CLASSIFICATION OF FARMLAND USING MULTITEMPORAL AERIAL IMAGES

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ABSTRACT:

It is well known that there is a growing need for consistent and up-to-date GIS-data at various scales for administrative and regulatory applications. Especially farmland classes are of high interest in this context. A new automatic method for the classification of crops is described. The method is based on sequences of digital aerial orthophotos with a ground sampling distance of 0.17m. The applied image sequence consists of twelve images of the same region within one vegetation period. Expert knowledge about the crops together with extracted features leads to temporal models for each crop. The temporal change of the features along with a changing relevance of a feature is considered. The temporal models are applied during classification that is based on a weighting function. The approach is tested on a test site of about 700ha and achieves correct classification rates better than 90%.

1. INTRODUCTION

The background of the paper is the observation and classification of farmland objects contained in present-day GIS data. Increasing demands for current and detailed information in GIS require the employment of automatic image processing techniques to reduce manual efforts when interpreting aerial images. Possible applications for such automatic processing are change detection, monitoring of fallow land and of erosion preventing actions. For the envisaged task, today image sequences of one vegetation period need to be manually interpreted by human operators.

This paper describes an automatic classification approach using multitemporal aerial images with a GSD of 0.17m and the spectral bands RGB. The approach is designed for the observation and classification of agriculture crops like summer and winter cereals, rape, meadow and forest. The classification is based on objects, where the borders are taken from an existing GIS. The workflow contains a feature extraction that is performed on single epochs followed by a classification step that regards the calculated features of all epochs together.

Considerable efforts have been carried out monitoring crop phenology from remote-sensing imagery in the last years [Törmä et al., 2007] [Shuai et al., 2008] [Vatsavai, 2009]. However, only few works that use a temporal model to guide the classification can be found. Current approaches [Feitosa et al., 2009] apply statistic models like Hidden Markov Models (HMM) that contain and model the temporal behaviour of the investigated crop classes. The statistic approaches model the temporal knowledge about the classes of interest implicit and have to be trained with a sufficient sample of test data.

Hence the classification in the proposed approach is based on explicitly formulated multitemporal models that are set up for each class separately. These models contain weights for each feature depending on the observation time and represent the relevance of a feature over time. The classification itself is done by calculating an evaluation measure which regards all available images of a scene during one vegetation period. The highest evaluation measure indicates the classification result for a farmland object.

The method is tested on a test site of about 700ha including 23 reference farmland objects of different classes. The corresponding multitemporal image material consists of 12 aerial image mosaics of the vegetation period between 2005 and 2006. For the test site correct classification rates of about 90% are achieved.

2. DATA USED AND TEST SITE

For the implemented approach, a rural test site that is intensively cultivated with different crops is chosen near the German city Rostock in the state Mecklenburg-Western Pomerania. An overview of the test site is shown in Figure 1. The aerial images were captured from a small aircraft with the low-cost system PFIFF [Grenzdörffer, 2005], developed at the University Rostock and the University Greifswald. The system has the advantage to be relatively weather independent. It can be used even in cloudy weather conditions. Therefore the acquisition dates can be predefined by the user quite accurately.

Figure 1 Aerial image of the test site near Rostock 2006-05-04

(the red boxes denote the 23 reference and the 18 other fields, see section 3.2)

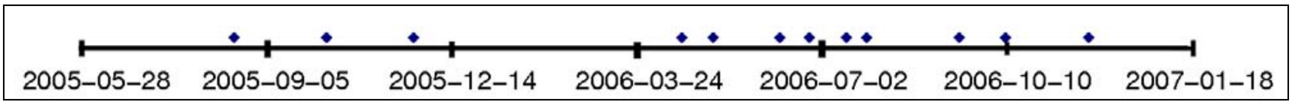

Figure 2 Acquisition dates of the image sequence

Two flights were made at each investigated date, the first with a small flying height resulting in an image resolution of 0.17m, the second with a larger height resulting in an image resolution of 0.47m. The used sensor has an infrared channel, but due to calibration problems, only the bands RGB could be used here.

The image sequence consists of images taken in the years 2005 and 2006 at the following dates: 2005-08-18, 2005-10-07, 2005-11-23, 2006-04-17, 2006-05-04, 2006-06-09, 2006-06-25, 2006-07-15, 2006-07-26, 2006-09-14, 2006-10-09 and 2006-11-23.

The time shifts between two images vary as depicted in Figure 2. During the growth periods of the cultivated plants more images were taken than during the remaining time. The investigated crops and land use types in the test site consist of eight classes; the classes corn, rape, winter wheat and meadow are dominant (ref. Table 1).

crop type/ land cover type	number of fields
spring barley	1
corn	8
winter wheat	3
oat	1
winter rye	1
rape	5
forest	1
meadow	3

Table 1 Crops and land use classes of interest and number of reference fields (see section 3.2)

3. APPROACH

The goal of the proposed approach is the assignment of a crop or land use class to regions with pre-defined borders. The segmentation of the regions is taken from an existing GIS and not subject of the paper. The approach works as follows: First numerical features are calculated for each region. To classify the regions into the classes of interest, temporal models are introduced, that represent the temporal behaviour of each investigated crop. A numerical feature vector is calculated for each region and for each image of the image sequence. All feature vectors together with the temporal models for each crop are considered simultaneously during classification. Here a comparison and evaluation based on the actual feature vectors and the temporal models is done, resulting in the most probable interpretation result. The next sections describe in detail the feature extraction, the generation of the temporal models and the classification method.

3.1 Feature extraction

The features that were chosen form the basis for the interpretation of the image sequence. They should represent the relevant characteristics that are also observable by a human operator for the classes of interest. Important items are the coverage degree, the growth stages and the human perception of the crops. This led us to choose the following features of spectral as well as structural features:

- Spectral features
  - green coloured pixel ratio
  - sand coloured pixel ratio
  - orange coloured pixel ratio
  - purple coloured pixel ratio
  - shade coloured pixel ratio
- Structural features
  - parallel lines

The spectral features represent the typical colour behaviour of a class. For spring barley an example of the colour behaviour is given in Figure 3. The colour changes from sand colour in springtime to green in the summer and back to sand colour during autumn.

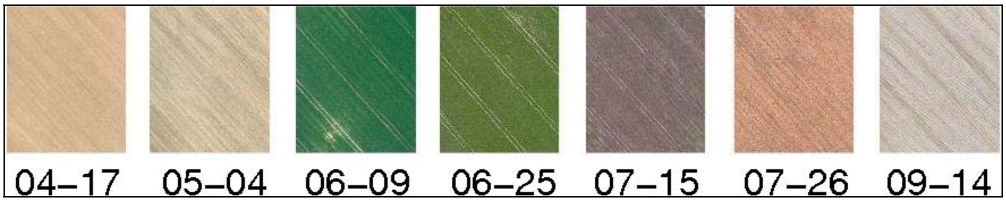

Figure 3 Image sequence of spring barley (2006)

The behaviour of the colour corresponds to the coverage degree (cp. Figure 4) and the growth stages (cp. Figure 5) for the specific crop. The colour ratios are calculated according to Equation 1 as the ratio of pixels belonging to a user defined colour class to the sum of all pixels of a region.

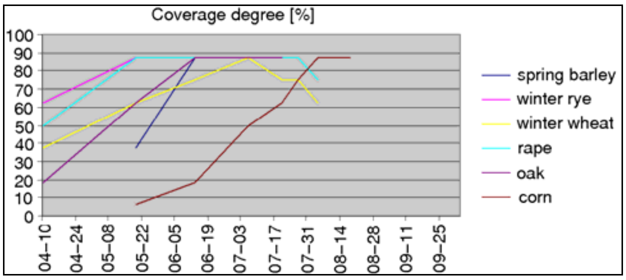

Figure 4 Coverage degree for investigated crops (2006)

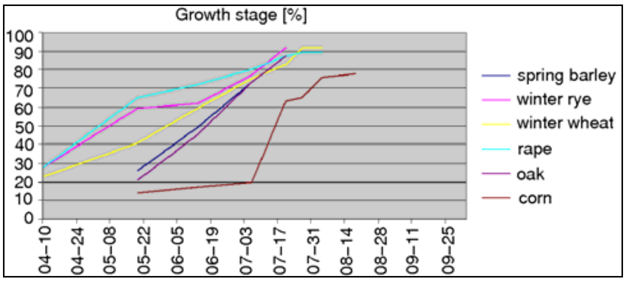

Figure 5 Growth stages for investigated crops (2006)

$$F_{color} = \frac{\sum_{region} pixel \subseteq color\ class}{\sum_{region} pixel} \qquad (1)$$

The detection of parallel lines caused by agricultural machines is based on the determination of texture parameters. For it the grey level co-occurrence matrix is calculated that delivers the local contrast in the image in the four directions 0°, 45°, 90° and 135°. If no parallel lines exist in the image (cp. Figure 6 lower row), the sign of the local contrast difference changes arbitrarily from one direction to the next considering all directions. If parallel lines exist (cp. Figure 6 upper row) the sign of the local contrast difference changes only once considering all directions.

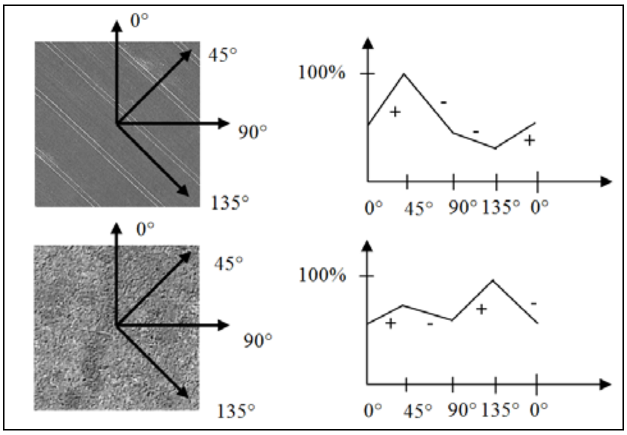

Figure 6 Direction dependency of local contrast

3.2 Temporal model

For each class of interest a temporal model is set up that represents first the behaviour of all introduced features over time and second the relevance of each feature over time. That means that one specific feature can be relevant for example in summer only, whereas another one only during springtime. In Figure 7 the systematics of the used temporal model is illustrated. The temporal models for the different classes of interest is determined based on the evaluation of 23 reference fields that are marked in Figure 1 with numbers and red boxes. Some of these fields were periodically inspected during the years 2005 and 2006. In addition expert knowledge about the crop growth was used to set up the temporal models.

In Figure 8 the resulting temporal model for the crop spring barley is illustrated. The grey box represents the relevance of 100% for all features between the 1st April and 30th September. This simplification of the relevance distribution was chosen to simplify the set up of the temporal models. In comparison to Figure 3 the fields appear in sand colour spring, in green during the summer, in purple during a short timeslot in July, in orange in August and again in sand colour in September. Parallel lines are visible from May to October.

The summer cereals spring barley, corn (cp. Figure 9) and oat (cp. Figure 10) have a live cycle from spring to autumn in one and the same year. The crops winter wheat (cp. Figure 11) and winter rye (cp. Figure 12) that are part of winter cereals as well as rape (cp. Figure 13) have a life cycle that begins in autumn and ends in the autumn of the subsequent year.

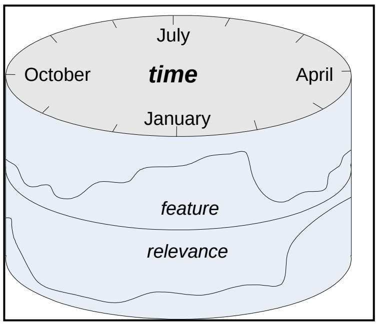

Figure 7 Temporal model

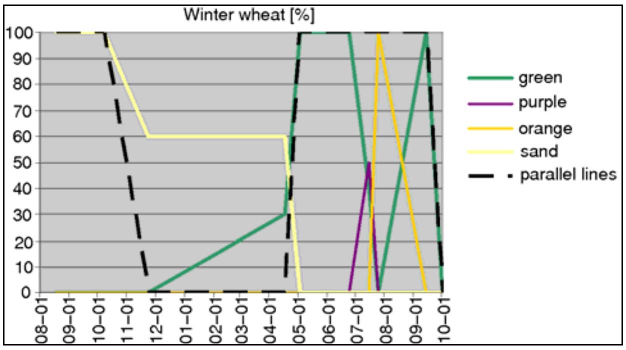

Figure 11 Temporal model for winter wheat

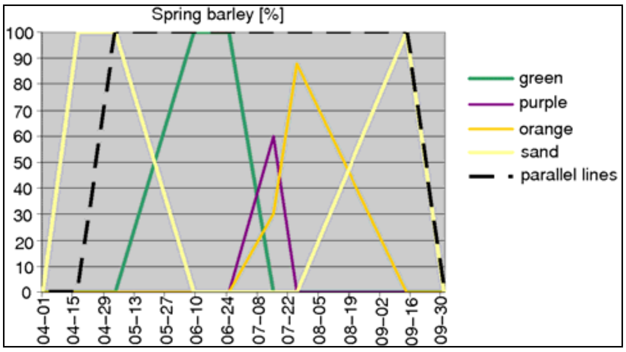

Figure 8 Temporal model for spring barely

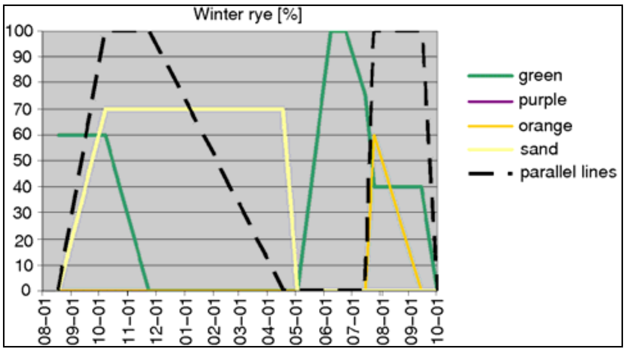

Figure 12 Temporal model for winter rye

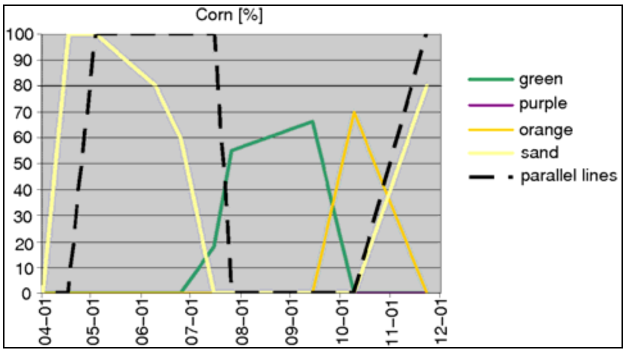

Figure 9 Temporal model for corn

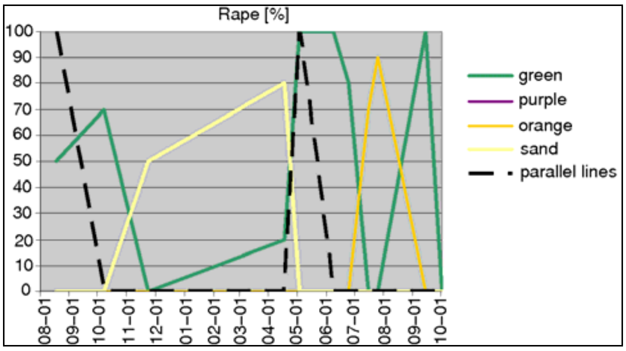

Figure 13 Temporal model for rape

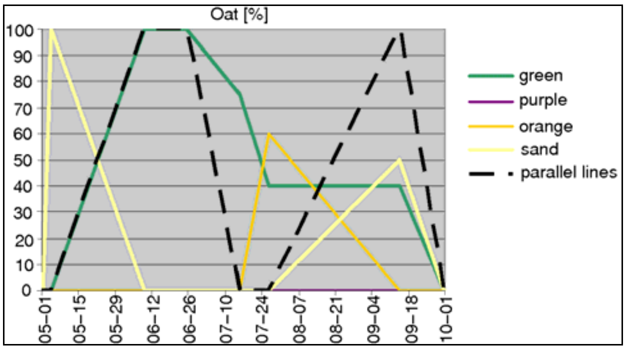

Figure 10 Temporal model for oat

3.3 Classification method

The classification is done with a weighting function (ref. Equation 2). A value Q_C is calculated for each class of interest a region could belong to. The class with the highest quality value indicates the classification result. The features are enumerated from *1* to *F*. For one value Q_C all features and all dates are considered as can be seen in Equation 2. The number of used dates is not predefined and can be adapted according to actual available data.

$$Q_C = \frac{1}{\sum_{f=1}^{F} W_{C,f}} \cdot \sum_{f=1}^{F} \left[W_{C,f} \cdot \frac{\sum_{i=t_1}^{t_n} R_{C,i} \cdot \left(1 - \Delta FF_{C,f,i}\right)}{\sum_{i=t_1}^{t_n} R_{C,i}} \right] \quad (2)$$

where

Q_C quality value belonging to class C

C assumed class for region

F	number of features
f	current feature
$W_{C,f}$	weight for current feature f and class C
t_1, t_f	first and last used date
i	current date
$R_{C,i}$	relevance of current feature f at date i for class C
$\Delta FF_{C,f,i}$	difference between observation and model for feature f, class C and time i [0..1]

4. RESULTS

The results are based on aerial images with a spatial resolution of 0.17m and the bands RGB. The test site is illustrated in Figure 1 and has an extent of 5km · 1.4km. Inside the test area 41 test fields are chosen (marked with red boxes in Figure 1). 23 of these fields are enumerated and represent the reference sample for the approach. The remaining 18 test fields belong to classes out of consideration. 9 fields of the reference sample were periodically inspected in 2005 and 2006. The remaining 14 fields are manually/ visually classified.
In the following the described classification method is applied to the data. For the training of the temporal models disjoint regions to the test sample were used. The classification result is illustrated in Table 2. The overall correct classification rate amounts to 91.3%, only two fields were misclassified in this test: one corn field was classified as meadow and one winter wheat field was classified as rape.

crop type/ land cover type	number of fields	wrong classified fields	correct classification rate
spring barley	1	-	100%
corn	8	1	87.5%
winter wheat	3	1	66.7%
oat	1	-	100%
winter rye	1	-	100%
rape	5	-	100%
forest	1	-	100%
meadow	3	-	100%

Table 2 Classification result

To test the significance of single features, the same test sample was classified again with the described classification method. The feature *parallel lines* is not considered for this test. The results are illustrated in Table 3. A strong decrease of the overall correct classification rate from 91.3% to 69.6% is observable. Now the class meadow could not at all be classified in this test. The meadow fields are misclassified as rape in this test.

crop type/ land cover type	number of fields	wrong classified fields	correct classification rate
spring barley	1	-	100%
corn	8	1	87.5%
winter wheat	3	2	33.3%
oat	1	-	100%
winter rye	1	1	0%
rape	5	-	100%
forest	1	-	100%
meadow	3	3	0%

Table 3 Classification result without feature *parallel lines*

5. CONCLUSIONS AND OUTLOOK

For the classification of farmland usually multispectral approaches are applied that work with spectral signatures and are trained with learning samples. If an image sequence is available, most often the data is stacked to a multilayer artificial image that is due to the number of bands difficult to classify.
The presented approach works with temporal models that include expert knowledge about the crops considering growth stages and observable features that are explicitly formulated. Due to the low impact of the input data on the models, they are easy to set up, to adapt and to expand. The classification result using all introduced features achieves correct classification rates better than 90%.
Obviously, the used test sample is quite small and the approach has to be tested and evaluated further. The transferability of the temporal models from one year to the next with changing climate conditions is at the moment not considered. The results show that the performance of the approach strongly depends on the feature collection: omitting of a single feature can affect the correct classification rate to a large extent.
In future the approach should be tested on additional crops to increase the number of classes that can be classified. Moreover the temporal models can be refined and expanded based on additional bands and features, especially the NDVI. Also the approach should be applied to high resolution satellite data including the search of suitable features under consideration of the reduced spatial resolution.

6. LITERATURE

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