MULTI-TEMPORAL SEGMENT BASED CLASSIFICATION OF ASAR IMAGES OF AN AGRICULTURAL AREA

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ABSTRACT:
A drinking water catchment area named "Fuhrberger Feld" in the north of Hannover in Lower Saxony is being studied to enable a reliable and continuous evaluation of chemical emissions from agricultural activities.
In this research and development project, ENVISAT polarimetric SAR data (provided free of charge by ESA within a pilot project "AO335") are used together with GIS information and ground surveys.
Due to only two possible polarisations of the data from the ENVISAT ASAR sensor, their coherence, together with the non-distinguishable response of different vegetation types and the high variance of the backscatter, a classification using single date images will fail or be far too inaccurate.
Methods like the use of multi temporal approaches have been tested to increase the classification accuracies.
In this paper, the feasibility of a classification method, based on the statistical behaviour of agricultural fields is discussed and an attempt is made to find an optimal combination of preprocessing and classification method. It has been found, that a priori maps or layouts of the agricultural field boundaries are a prerequisite for the method which tries to define the crop type on the base of an existing segmentation. Test results from the years 2004 and 2005 are presented in this paper. An accuracy of 85% is achieved using 11 images of year 2004. However, using only 6 available images in the year 2005 reduces the accuracy down to 64%..

1. Introduction

The "Fuhrberger Feld" is situated north of Hannover the capital from Lower Saxony. The water quality reports of the past years of the lower Saxony state office for water and refuse state in numerous locations groundwater nitrate values above the drinking water-threshold of 5 to more than 50 mg nitrates per liter. These values reflect a strong threat to the quality of the drinking water extraction.
Since pastures and agricultural fields are important possible sources of chemical emissions and because the area is intensively cultivated or utilised as pasture, nitrate emissions depend strongly on the type of crop being cultivated [Walter et al., 1998]. Therefore it is required to monitor the area continuously. Considering the very high costs of classical surveying methods including also aerial photography, the use of space based data is favoured [Redslob et al., 2000]. Because of the frequently cloud cover in the study area ASAR data from ENVISAT Satellite are selected to monitor the agricultural activities.
This however induces some problems, like:
- The number of polarisations, which is small compared to the number of bands of images from optical sensors. This makes the available multi dimensional feature space of radar images very small.
- Different bands (polarisations) are sometimes more correlated than spectral channels of optical images.
- The speckle, especially in SAR images, results in a large variance within the training samples yielding an unsatisfactory classification.
- Spatial resolution of radar images is often not as good as of images from passive systems under similar conditions.
- Radar images are strongly affected by look angle influences, soil moisture and physical properties of the soil. These dependencies often affect signatures more than vegetation specific influences.

The most important advantage of radar systems is their (almost) independence to the weather conditions and therefore data can be acquired irrespective of cloud cover. Because of this fact more frequent usable images and better temporal resolution is available. In addition SAR images can sometimes prove to be better suited than optical images [Matthaeis et al., 1995, Yakam-Simen et al., 1998].
A variety of papers demonstrate how to overcome these limitations and make use of the benefits of SAR images.
Numerous filters are offered [Nezry et al., 1995] and evaluated [Dewaele et al., 1990, Lehman et al., 2004] in order to reduce speckle of radar images, while keeping details, edges and statistical parameters unchanged.
In order to classify crops, it is tried to use all available polarisations [Kreisen et al., 2002, Nezry et al., 1995], multi-temporal data [Hochschild et al., 2005, Tröltzsch et al., 2002], object based classification techniques, combination of passive data [Hochschild et al., 2005], knowledge driven classification [Habermyer et al., 1997] and the evaluation of the effects of local characteristics on radar images [MCNarin et al, 2002.]. Using these methods an accuracy of 70% to 90% is achievable in agricultural areas. But results of different crops don't have the same reliability. Some crops can not be classified satisfactory others do [Habermyer et al., 1997].
As reported in [Lohmann et al., 2005, Tavakkoli et al., 2006.] tests using single radar images (VV/VH amplitude images) show an unsatisfactory interior accuracy of only 25% to 35% using the raw data only and about 30% to 45% using filtered data. The accuracy of the results is highly time-dependent for different crops and image dates
On the other hand, the use of multi-temporal data resulted in an interior accuracy of up to 100% and exterior accuracy over 80% on average.

2. Data

2.1. Images

The images used are radar acquisitions with the VV and VH polarisation of the ENVISAT ASAR sensor with about 30 meters spatial resolution and 12.5 Meters pixel size. All images are from descending orbit and the swathes used range from 5 to 7. A total of 17 images are available for the years 2004 and 2005 which are listed in table 1.

2.2. Ground surveys

About 50 fields have been selected to be used as references, covering the existing crop types of that area. Each field was required to be relatively homogenous in its extent and large enough in any direction.
The study area has been inspected close to each acquisition date. Information, which has been gathered for each field in each inspection of the study area, is:

- Land use
- Farming direction
- Distance between rows
- Weather condition
- Land and farming activities situation
- Vegetation coverage %
- Vegetation height
- Land and vegetation moisture
- Condition of vegetation
- One or two photographs
- Position and geometry of the field (due to farmer's activity the geometry can vary between the inspections)

Nr.	Image Date	Inspecting Date	Orientation
1	17.11.2003	26.11.2003	Descending
2	17.03.2004	19.03.2004	Descending
3	05.04.2004	05.04.2004	Descending
4	21.04.2004	21.04.2004	Descending
5	10.05.2004	10.05.2004	Descending
6	26.05.2004	10.05.2004	Descending
7	30.06.2004	14.06.2004	Descending
8	07.08.2004	07.08.2004	Descending
9	11.09.2004	08.09.2004	Descending
10	13.10.2004	13.10.2004	Descending
11	01.11.2004	01.11.2004	Descending
12	06.12.2004	06.12.2004	Descending
13	02.03.2005	02.03.2005	Descending
14	09.04.2005	08.04.2005	Descending
15	18.06.2005	15.06.2005	Descending
16	12.09.2005	12.09.2005	Descending
17	21.11.2005	21.11.2005	Descending

Table 1: Data takes of ENVISAT ASAR APG images, polarisation VV/VH, IS 5-7

2.3. Map of the fields

It is necessary to create a separate layout map for each inspection, because the field borders are not always fixed and change frequently. Therefore, some fields may become too small to be used with respect to the resolution of the images and have to be eliminated, and other fields are added in order to keep record of the most important farming activities.
Considering the 30 meters spatial resolution, a 30 meter strip has been eliminated (buffered) from the boundary of each field to keep each training field as homogenous as possible and to eliminate mixed or unreliable pixels from the statistics. These maps then are used in the further processing.

3. Preprocessing

Speckle in radar images reflect physical properties of microwaves together with instrumental errors and target properties. This means that the speckle may be a meaningful variable reflecting the behaviour of different surfaces. On the other hand it influences strongly the statistics of an image. Therefore the question arises, if the images should be filtered or if the speckle can be used to make fields more comparable for classification.
A Lee filter with a 7x7 kernel has been used as an example of a despeckle filter in order to investigate if despeckled images are better suited for the suggested method. The kernel size (7x7) has been chosen with respect to the resolution (30 meters) and pixel size (12.5 meters). Therefore a 7x7 filter on an image with 12.5 meters pixel size covers an area of 87.5x87.5 m^2, which is comparable to a 3x3 kernel for the 30 meters resolution, and represents the smallest meaningful kernel size for this resolution.

4. Classification

Considering the (almost) independence to the weather conditions, SAR data can be acquired irrespective of cloud cover. Because of this fact, more frequent usable images and therefore better temporal resolution and an extended feature space becomes available. Because of potential higher temporal resolution, SAR images sometimes are to be better suited than optical images as reported in de Matthaeis et al., 1995 and Yakam-Simen et al., 1998.

4.1. Classification of single date images

To test the ability of classical classification methods on single date ASAR images, we have tested different classification methods on two-band single date images. As result, only 20-30% of sample fields have been correctly classified using unfiltered images (interior accuracy). The interior accuracy of the classification of filtered images increased to 25-45% using sample fields, depending on the method of filtering and the date of acquisition. We did not find any important effect on the results concerning the classification method. [Lohmann et al., 2005].
It is noticeable that the accuracy of classification is strongly dependent on land use type and acquisition date, i.e. each crop can be recognised on some images better than on other images and on the other hand from each image some crops can be extracted better than other crops. As can be seen on Figure 1, some crops such as pea, strawberry and winter grains are classified relative well but others do not, using the image taken on 10.05.2004.

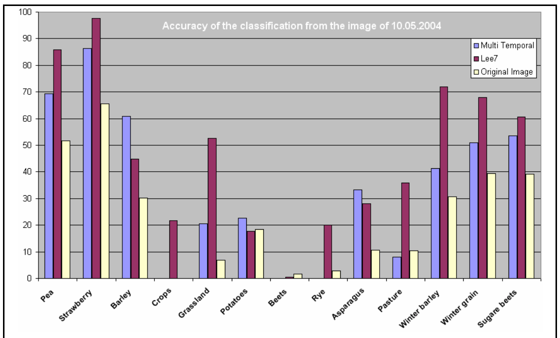

Figure 1: Accuracy of classification using filtered (multi temporal and Lee) and unfiltered images from 10.05.04

4.2. Pixel based multi-temporal classification

Multi-temporal classification of SAR data is a well known method for overcoming the limitations of SAR data and improving the accuracy of classification.
The multi-temporal approach becomes possible because of the independency of SAR from weather conditions, making it possible be applied more frequently and reliable in comparison to optical images.
Due to the changeable nature of agricultural fields, each crop has its specific growth period and therefore can be separated from other crops. Thus the changes of fields of one crop can be used as a signature of the crop.
This method has been vastly used and tested in different countries and for different crops [K.Tröltzsch et al., 2002, in Mali, V.Hochschild et al., 2005, Schieche et al., 1999, in Germany, Baronti et al., 1995 in Italy, Foody et al., 1998, in England and Davidson et al., 2002,in Japan]
We found, the exterior accuracy of multi-temporal classification in our study area to be between 55% to 98% for different crops with an average of 83% when proper sets of despeckled images are classified using proper signatures [Tavakkoli et al,.2006].

4.3. Segment based multi-temporal classification

Each field can be considered as a homogenous segment with patterns of vegetation on agricultural fields which are very fine compared to the resolution of ASAR images (30 meters). Distances between rows of cultivation are between 12cm (grains) and up to about 200cm (asparagus) and often rows can not be recognised for some crops such as pastures, grass and rapes.

Especially, when crops grow up and the canopy covers all the area a pattern is rarely visible.

Besides the absence of patterns on ASAR images, hardly any significant effect from cultivation rows and their direction can be recognised on the fields statistics of this area. As shown in [Cong X. 2005], the direction of rows does not significantly affect the fields statistics even with fields of asparagus and potatoes, which not only have wide rows but also hills of soil.

In addition, speckle in SAR data prohibits appearance of fine patterns and contexts. Appling despeckle filters suppresses the patterns together with the speckle. Therefore, an object oriented classification based on patterns and texture of agricultural fields with images of 30 meters resolution is not very successful.

There are only a few examples for attempts of object oriented classification of SAR data. R. Heremans et al. [2005] detected flooded areas on ENVISAT/ASAR images using object oriented method of eCognition software. Sun Xiaoxia et al. [2006] classified airborne SAR data enhanced with optical data of SPOT5 using object oriented method offered by eCognition software and reported better results in comparison to pixel based classification on the same data set.

We tried to evaluate the accuracy and possibility of a segment (field)-based classification using statistics of agricultural fields.

4.3.4. Methodology

Tables of means (M) and standard deviation (SD) of pixel values covering the extent of sample fields in sets of multi-temporal ASAR images are computed to be used as signatures. Table 2 represents a small part of one signature table. There is at least one record for each crop. Each column represents statistics (M or SD) of sample fields on each band (VV or VH) of multi temporal set of images. e.g. column “M_L1 17.11” represents Mean values (M) of band VV (L1) of the image taken on 17.11.2004.

The values of each record represent the average of the statistics (M or SD) obtained from one field, which is covered by the desired crop during the time of imaging. Therefore each record is a multi temporal statistical signature of one crop. The value -1 means that the desired crop was not cultivated at the time of imaging in the study area.

Crop	M_L1 17.11	SD_L1 17.11	M_L2 17.11	SD_L2 17.11	M_L1 17.03	SD_L1 17.03
Lea	292	80	170	47	293	32
Fallow	358	97	154	37	351	36
Peas	-1	-1	-1	-1	-1	-1
Strawberry	456	122	188	43	460	38
Willow	272	82	144	32	292	32
Potato	-1	-1	-1	-1	-1	-1
None	387	97	166	43	389	33
Summer grains	-1	-1	-1	-1	-1	-1
Asparagus	321	105	149	33	331	47
Pasture	284	86	138	36	281	31
Winter grains	314	90	131	32	317	28
Sugar beets	-1	-1	-1	-1	-1	-1

Table 2: A part of one signature table used for multi-temporal segment-based classification

In the next step, the multi-temporal statistical signature has to be compared with the multi temporal statistics of each sample field and the field has to be assigned to the most likely crop. For this comparison, we have to calculate the distances between statistics of one field and each record of the signature table separately as a similarity factor.

Since the absolute distance between the statistics of a field and the statistical signature of a crop (a record of signature table) is a vector of differences and not a single value, the distances (d) from different images have to be merged to form an absolute distance value (d_c) between the statistics of a field and the statistical signature of a crop.

Two methods are tested to calculate d_c:

1- Using a simple distance method, which calculates summation of elements (d) of one distance vector.

$$d_c = \sum_{n}^{i=1} d_i \quad (1)$$

2-Another distance method is Euclidian distance which calculates the root of summation of square of distances (d).

$$d_c = \sqrt{\sum_{n}^{i=1} d_i^2} \quad (2)$$

Each of these equations converts one distance vector to a distance value (d_c). The first method calculates a simple summation of elements of one distance vector while the other considers the elements of the distance vector as distances between coordinates (x, y, z …) of two points (one point is the field the other a record of the signature table) in an n dimensional space and calculates the spatial distance between two points as a distance value. The difference between both methods becomes more obvious on large values because the second method exaggerates large values. For example the distance vectors A (10, 10) and B (5, 15) are calculate by the first method as:

A=>20

B=>20

But from second method:

A=>14.14

B=>15.81

Therefore using the second method a large distance value affects the result more than some small distances with the same summation. Therefore a deviating statistical value from one image (date) compared to the signature values will be exaggerated using the Euclidian method. In order to test their suitability we tested both methods using different sets of data.

Considering that the growth period for different crops is not identical and taking into account that some types are planted for only two or three months while others remain for a whole year, the calculated distance values have to be normalised through division by the number of elements of the distance vector.

The normalized distance thus is given by:

$$d_{cn} = \frac{d_c}{n_c} \quad (3)$$

Where:

d_{cn}: Normalized distance between statistics of one field and statistics of one crop

d_c: Absolute distance value between statistics of the field and statistics of the crop obtained from (1) or (2)

n_c: The number of valid values (images in growth period) in the signature record of the crop

Figure 2 shows the cultivation period of different crops in the study area for the year 2004. Images related to this cultivation period are used for classification in 2004 and a similar table can be set up for classification of the year 2005 using 6 images.

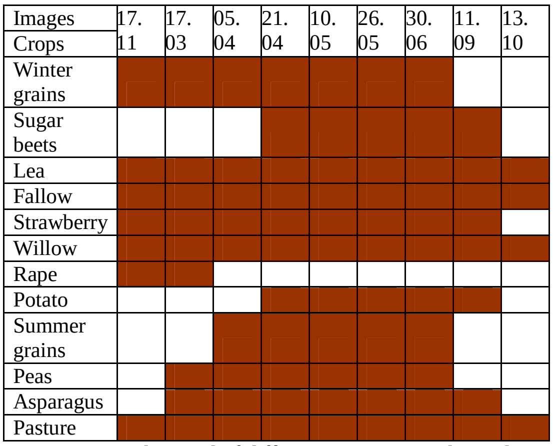

Figure 2: Growth period of different signatures in the study area between Nov. 2003 and Nov. 2004

Rape has a different phenological period compared to other crops. A fixed phenological period for rape in summer can not be observed because often rape is cultivated as fertilizer and hence depends on the calendar of the other crops. Winter rape often is cultivated in September or October and harvested before March. Therefore we considered the time between November and March as phenological period of rape and used the images of: 17.11.2003, 17.03.2004, 06.12.2004 and 02.03.2005 for the classification of rape.

It can be seen from Figure 2 that it is possible to have rape and another crop e.g. sugar beets on one field, because they have different phenological periods. Therefore the classification process must be able to account for more than one class per field, if crops with different phenological periods are cultivated on the same place.

4.3.5. Preprocessing

Different preprocessing of the original images has been tested in order to check the classification accuracy using different types of input data. The techniques are listed in table 3 and a reference numbers are assigned to each one to be used for referencing. PCA in table 3 is the first principle component between two bands (VV and VH) of each image. ND is normalized difference between two bands (VV and VH) of each image, which is calculated as:

$$\frac{VV - VH}{VV + VH}$$

Ref. number	Preprocessing
1	Original (no preprocess)
2	Filtered Image
3	PCA from Original
4	PCA from Filtered
5	ND from Original
6	ND from Filtered

Table 3: Preprocessing techniques tested in this study

4.3.6. Test of Method and data combination

Different combinations of input data (1 to 6 of table3), statistics (M and SD) and distance methods (simple or Euclidian) were used to investigate which combination of data, statistics and classification method is optimal. To do this, statistics from each field were compared with statistics of each crop during the growth period of that crop (signature table) in the year 2004. The crop type having the closest statistics to desired field is assigned to the field within the growth period of the crop.

This classification method is tested using sample fields to evaluate the accuracy of the method in this area. The accuracy is evaluated based on results for crops with a fixed and known growth period, for which more than one training sample were available.

The multi-temporal classification method can not be used for crops without a known phenological period. On the other hand, we are comparing statistics of signatures with statistics of fields by applying this segment-oriented classification method. Therefore it is not acceptable to evaluate the accuracy of classification for one crop if only one sample is available for it. In this case the accuracy for the crop would be 100%, which is not reliable.

Because in winter, winter grains are more similar to bare lands and they appear like summer grains in summer and because different grains have similar phenological periods and characteristics, there is a high degree of mixture analyzing the results of winter and summer grains and with respect to different grains as well. The accuracy of classification of winter and summer grains as one crop species can be tested under this condition too. Classification accuracies of using different combinations of data and distance methods are presented in table 4.

As can be seen from table 4, the best accuracy is achieved when the mean of all preprocessed data is classified using the simple distance method (SD, 1-2-3-4-5-6, M). The accuracy of the filtered data is improved when they are classified using the Euclidian distance method, especially if all grains are assumed as one crop.

Generally the classification result using original data (without preprocessing) is more accurate if classified by using the simple difference method, but preprocessed data (filtered, PCA, ND) often is superior classified using the Euclidian distance. One reason is assumed to be the speckle, since, as noted before, the Euclidian Method exaggerates anomalies caused by speckle in unfiltered images but preprocessed images are occasionally despeckled.

Input Data	Accuracy (Grains separated)		Accuracy (Grains merged)	
Preprocessing (Tab.5) ,Statistics	Simple Distance	Euclidian Distance	Simple Distance	Euclidian Distance
1,M	0.84	0.83	0.85	0.88
1,M-S	0.82	0.82	0.85	0.88
2,M	0.84	0.84	0.88	0.89
2,M-S	0.83	0.86	0.86	0.91
3,M	0.65	0.64	0.68	0.69
3,M-S	0.62	0.72	0.68	0.77
4,M	0.59	0.63	0.65	0.69
4,M-S	0.55	0.63	0.62	0.69
1-5,M	0.86	0.83	0.88	0.88
1-5,M-S	0.86	0.82	0.88	0.88
2-6,M	0.85	0.86	0.88	0.91
2-6,M-S	0.83	0.86	0.86	0.91
1-2-3-4-5-6,M	0.89	0.83	0.91	0.88
1-2-3-4-5-6,M-S	0.85	0.82	0.88	0.88

Table 4: Accuracies evaluated from results for crops with fixed and known phenological period

PCA and ND are not classified superior to the primary bands (VV and VH) of the SAR images but when combined with primary bands the accuracy is slightly improved.

Considering all grains as one crop improves the total accuracy of classification as expected, because a mixture between grains is not anymore considered as an error.

Using mean and SD instead only the mean of fields does not improve the accuracy of classification in many cases.

4.3.7. Applying the Segment-Based Classification Method to Sample Fields

In a next step the segment-based method is applied to sample fields of all crops in order to test the method for the case that all crops with fixed and known phenological period are classified and not only those crops, for which more than one sample is available.

It could be shown (table 4) that in general classification of filtered images is more accurate than using only the original images and using PCA and ND does not efficiently increase the accuracy of the results. Therefore, the statistics (mean and SD) of filtered data are processed using Euclidian distance method in this phase.
Table 5 represents accuracy of the results together with the number of available samples for each class using 11 images out of the year 2004. As can be seen single samples (yellow records) are exactly recognised and the average accuracy value of crops with more than one sample is 85.2%, which is not constant for all crops. Table 6 shows the same information but all types of grain are considered as being one crop type in order to investigate the accuracy level if the class "grains" would be accepted by some applications. As expected, accuracy value is higher if all the grains are classified as one class. In this case, 88% of the crops, for which more than one sample is available, are correctly classified.

Class	Accuracy	No. Of Samples
Lea	1.00	1
Fallow	1.00	1
Peas	1.00	1
Strawberry	1.00	1
Willow	1.00	2
Potato	0.68	6
None	1.00	2
Rape	1.00	1
Summer barley	0.76	5
Summer rye	1.00	1
Asparagus	1.00	4
pasture	1.00	6
Winter barley	1.00	5
Winter rye	0.57	7
Winter wheat	1.00	1
sugar beet	0.66	9

Table 5: Accuracy of segment-based classification for crops in the study area for year 2004. (Average accuracy: 85.2%)

Class	Accuracy	No. Of Samples
Lea	1.00	1
Fallow	1.00	1
Peas	1.00	1
Strawberry	1.00	1
Willow	1.00	2
Potato	0.68	6
None	1.00	2
Rape	1.00	1
Asparagus	1.00	4
pasture	1.00	6
sugar beet	0.66	9
Grains	0.82	19

Table 6: Accuracy of segment-based classification for crops in the study area when different grains are considered as one crop for year 2004. (Average accuracy: 88%)

Tables 7 and 8 show the accuracy and number of available samples for each class using 6 images of the year 2005. The major difference between the classification of images of 2004 and 2005 is the number of available images. Only 6 images for the year 2005 are used which results in a poor average accuracy of 64% Another difference is that there are 3 fields of maize and 6 fields of rape which are well classified in the year 2005 but there were no Maize field and only one rape field in the year 2004.
Table 8 shows the accuracy of results for the data of year 2005 with all grains classified as one crop. 75% of sample fields are correctly classified in this case. This shows an improvement of 11% in comparison to the values of table 7 (different grains separated); while there is only less than 3% difference between accuracy of the two representations of classification in the year 2004 (tables 5 and 6). This indicates a high value of mixture between different grains, which is caused by the small number of images for the year 2005.

Class	Accuracy	No. of Samples
pasture	0.81	5
maize	1.00	3
sugar beet	0.47	5
Winter rye	0.36	9
Fallow	1.00	1
Winter barley	0.35	8
Asparagus	0.44	4
Summer barley	0.42	8
Potato	0.71	4
Willow	1.00	2
Peas	1.00	1
Lea	0.51	2
Summer Wheat	1.00	1
Summer oat	1.00	1
Rape	1.00	6

Table 7: Accuracy of segment-based classification for crops in the study area for year 2005. (Average accuracy: 64%)

Class	Accuracy	No of Samples
pasture	0,81	5
maize	1,00	3
Rape	1,00	6
Sugar beet	0,47	5
Grains	0,84	27
Fallow	1,00	1
Asparagus	0,44	4
Potato	0,71	4
Willow	1,00	2
Peas	1,00	1
Lea	0,51	2

Table 8: Accuracy of segment-based classification for crops in the study area when different grains are considered as one crop for year 2005. (Average accuracy: 65%)

5. Conclusion

A segment-based classification method based on the statistics of agricultural fields is evaluated and applied over the study area for years 2004 and 2005. It could be shown that the number of used images efficiently affects the results. A good segmentation of images or a layout map of agricultural fields in the study area is necessary to apply this method of classification, because this method is based on field specific statistics and thus is impossible without any field map. A wrong map or poor segmentation of images therefore can strongly decrease the classification accuracy.

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