OPTIMIZATION OF AGRICULTURAL CROP IDENTIFICATION IN SLAR IMAGES: HIERARCHIC CLASSIFICATION AND TEXTURE ANALYSIS

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ABSTRACT

In 1980 a large SLAR flight program was carried out over an agricultural area in The Netherlands. A classification study on this multitemporal dataset (Ref. 1) showed that high accuracies are obtained from a simultaneous classification of 3 flights. In this paper the results of a follow-on study will be discussed. The goal is to obtain the best possible classification result in the earliest possible stage of the growing season. Therefore the SLAR flights from April, May, June and July were analyzed and the hierarchic classifier is introduced. Very satisfying results were obtained from a combination of 3 flights: 1 in May, 2 in July at different incidence angles.

In a next part of this paper, within field texture is investigated as a possible extra feature. Texture measures were determined from the Gray Level Co-Occurence Matrix (Ref. 2), which is known to be rather sensitive for small texture elements, in the order of pixel dimensions. Sofar the within field variations do not seem to contribute substantially to a classification process.

1. INTRODUCTION

In this paper the results will be discussed from a follow-on study on previous classification experiments (Refs. 1, 3). This study forms a part of a broader national remote sensing research program for agriculture and forestry, carried out by the ROVE-team (Radar Observation on VEgetation), a collaboration of several institutes (Ref. 1). This study was carried out in a cooperation between the Information Theory Group of the Delft University of Technology and the Physics and Electronics Laboratory TNO (formerly Physics Laboratory TNO) in The Hague.

The testsite on which the study is performed is situated in the Flevopolder, a reclaimed land area. Figure 1 shows a part of this polder, including the testarea. The latter contains 195 agricultural fields, of which 164 were suitable for this experiment (crop type known, reasonable dimensions). Frequently used crop types in this area are winterwheat, potatoes and sugarbeets (80 % of total area). Onions and peas are also important crop types, but grown on smaller fields and therefore make up only 8.5 % of the area. These 5 most occurring crop types were used in designing the classifier.

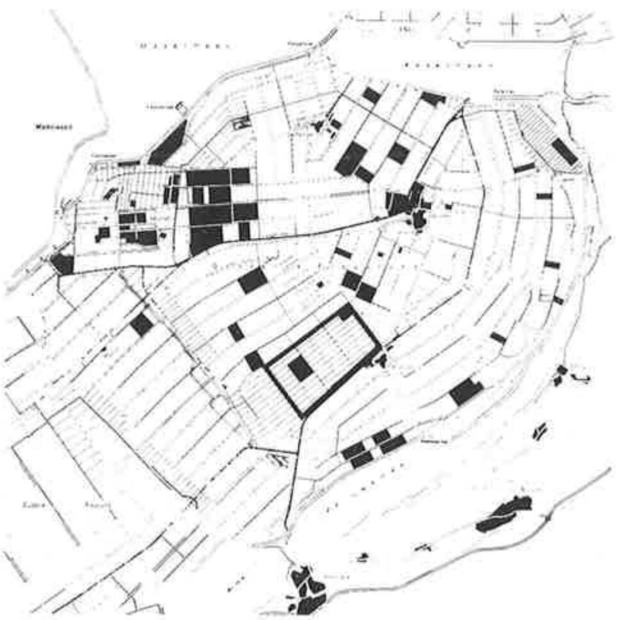

Figure 1. Map of the Flevopolder with the testarea indicated (near 'Biddinghuizen'). The map shows an area of 35 x 35 km. The testarea measures 3.7 x 6.2 km.

The area was imaged with an X-band SLAR system, using digital recording, on 5 different dates throughout the growing season. At each flight date recordings were made from 3 different altitudes, resulting in 3 incidence angle ranges, and from 2 opposite sides of the testarea. This flight campaign resulted in a multitemporal and multiangular database of the area. A selection of these flights is shown in fig. 2. The development of the radar backscatter through time can be viewed from this selection. The sampling interval is appr. 1 month. For July two images are shown: one is flown at 660 m altitude, like the other images shown, which results in a grazing angle range from 7.5^0 to 16^0 (right to left in the images). The second July image is flown at 1600 m, resulting in grazing angles between 18^0 and 35^0.

For comparison a croptype map is shown in figure 3. This figure results from the radar images, after

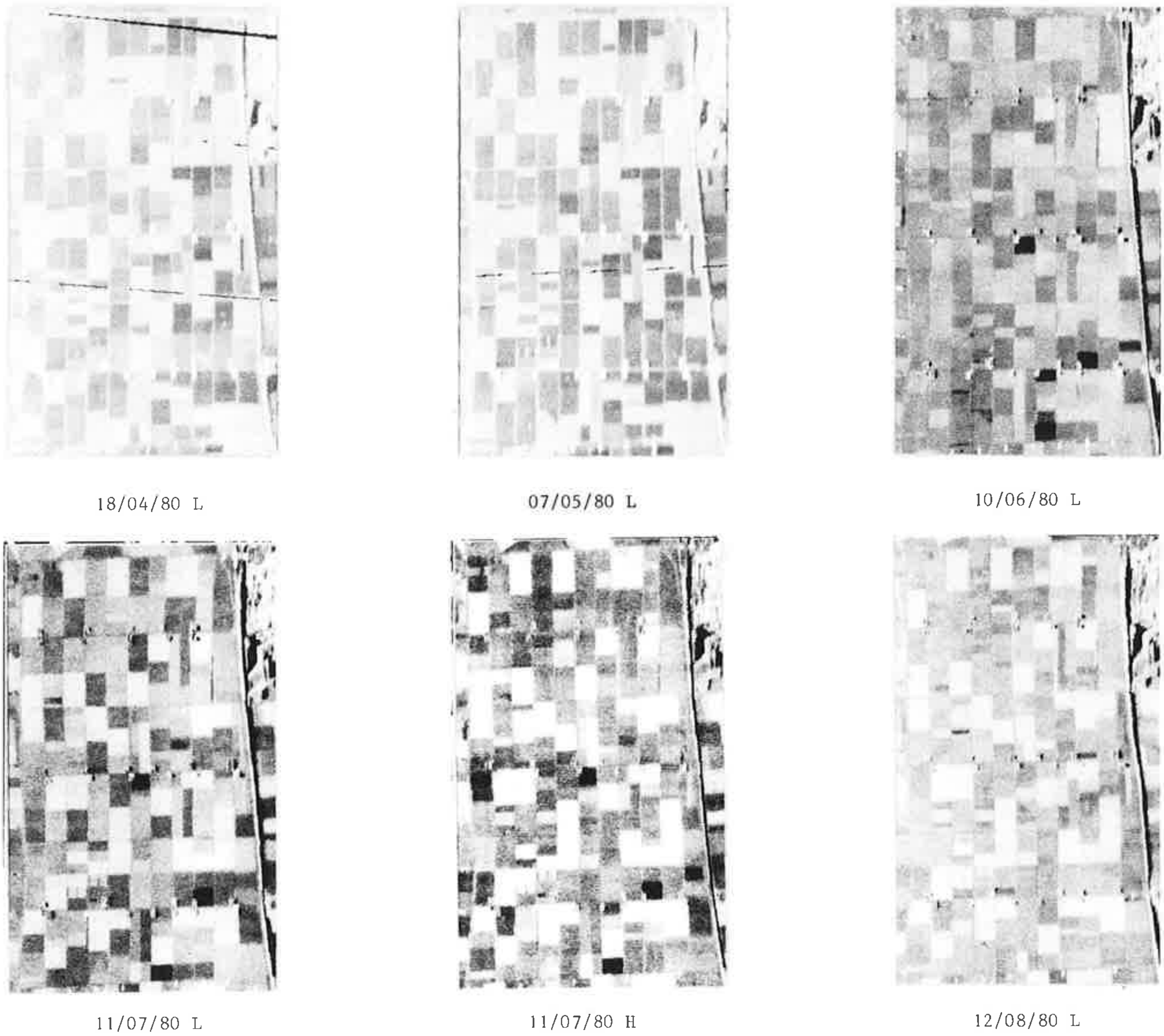

Figure 2. X-band SLAR flights over the testarea on the indicated dates. Dimensions: 3.7 x 6.2 km.
L = low altitude, 660 m (16^0 - 7.5^0 grazing angle)
H = high altitude, 1600 m (35^0 - 18^0 grazing angle)

registration and field segmentation. The segmentation is done manual by drawing the field boundaries in the image on an image processing system. Only the 3 main croptypes could be indicated here, because of the limited separability of gray tones in a black and white image after reproduction. However 80 % of the area is covered by these 3 croptypes.

The advantage of field segmentation of the radar data is two fold:

1. The influence of speckle on the classification result is reduced to practically zero. This also holds for small inhomogeneities within the fields.
2. The amount of data is tremendously reduced, since we end up with one value per image for every field, thus 164 values for one image.

For the classification experiment the radar data of the 6 mentioned images were combined with the groundtruth into one datafile. For every field there are 7 features, i.e. the true field label (croptype) and 6 average backscatter coefficients.

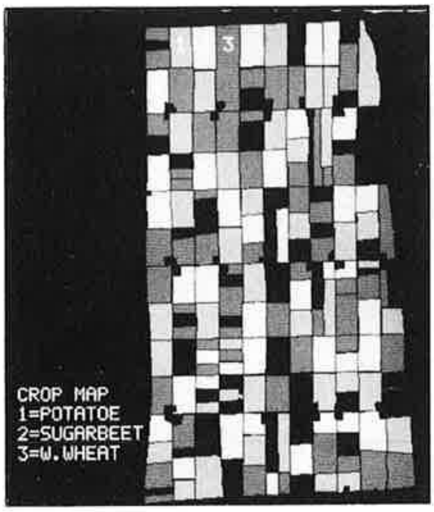

Figure 3. Croptype map of the testarea for the 3 main croptypes.

2. CLASSIFICATION EXPERIMENT

The purpose of the experiment was to design a classifier on basis of the radar data of the 5 most important croptypes. The classifier should be able to distinguish between these croptypes as early as possible in the growing season. This is different from the previous experiment (Ref. 1), where we used the flights of June, July and August for classification. For operational applications an early result would be much more useful. Certainly, an improvement over the older experiment should be possible, considering the high contrast in the early season flights (fig. 2, April and May). Figure 4 shows the development of the radar backscatter coefficient throughout the growing season for the 4 most important croptypes. Although the digital

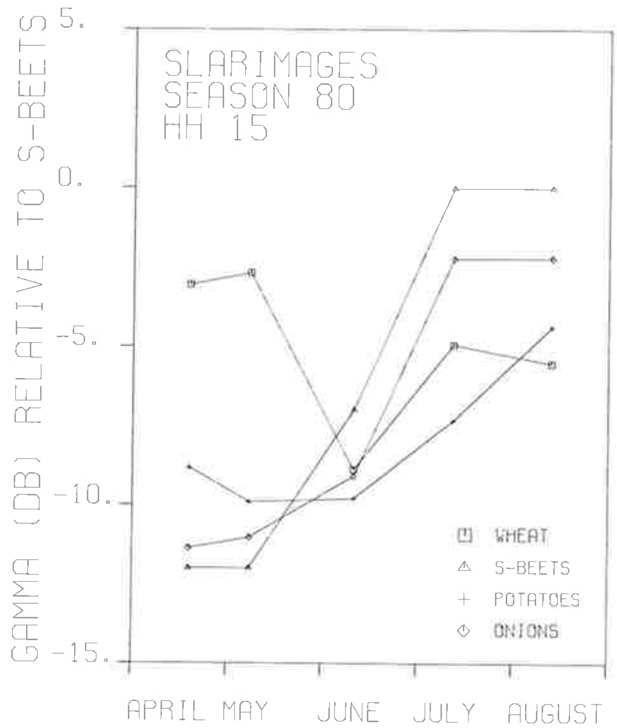

Figure 4. Development of radar backscatter throughout the growing season for some croptypes. X-band SLAR, horizontal polarization, 15^0 grazing angle.

radar images have known intensity scales, an absolute calibration lacks in these measurements. Therefore the average backscatter coefficient of the sugarbeet fields was determined in the images and compared to calibrated ground based measurements, which were always taken at the same date and in the same area. The resulting correction-factor was applied to the whole image. The data in figure 4 is for horizontal polarization and 15^0 grazing angle. The frequency is 9.4 GHz (X-band).

From figure 4 it can be seen that a large contrast exists between winterwheat and the other croptypes in April and May. In June the contrast is very small, while all the crops are in their growing stage. In July a good contrast is present between all the croptypes, whereas in August the development of the backscatter coefficient of potatoes interferes with the one for winterwheat.

The large contrast between winterwheat and the other croptypes in the early growing season only exists at low grazing angles. It can be explained as follows: the wintercrops, like winter-wheat, are planted before winter and start growing in this area in April. The other croptypes are planted in April and May an show their biomass not before the end of May. Although the ground coverage by the new plants is small, the backscatter at low grazing angles is increased, because the smooth soil alone gives a very small amount of backscatter at these angles, so the small leafs sticking out of the ground contribute considerably to the total backscatter. At larger grazing angles say around 40^0, the backscatter from the fields is much increased and the previously described effect is smaller, resulting in very little to no contrast between these croptypes.

Thus we should be able to distinguish between winter- and summer crops from one flight in April or May, and since our testarea contains mainly one wintercrop, namely winterwheat, we should be able to identify all winterwheat fields. Figure 5 shows the histogram of the field averaged radar backscatter coefficients of the SLAR image from May. From this

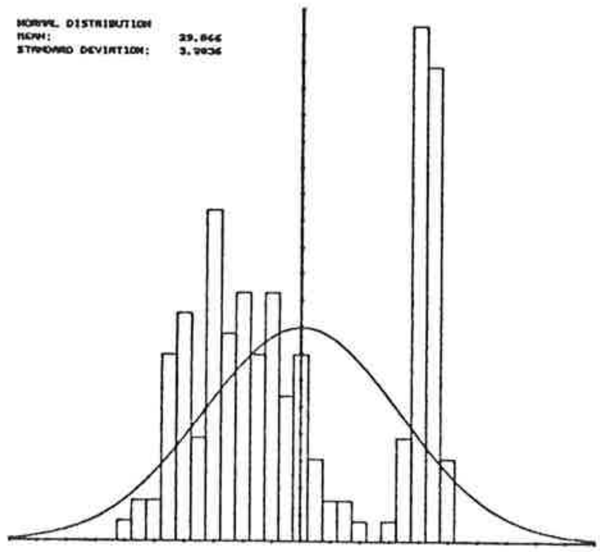

Figure 5. Histogram of the May flight: winterwheat (right) is separated from the other croptypes.

figure it is clear that the winterwheat fields can be completely separated from the other fields, simply by applying a threshold level.

Now that the winterwheat is identified, we must try to classify the remaining fields from other flights. This demonstrates the hierarchy in our classifier in contrast with the previous classification experiment (Ref. 1) where the time dependence of the radar backscatter throughout the growing season was used as discriminator.

Sofar the design of the classifier was straight forward and rather simple. However to derive an optimum result more elaborate methods should be used to investigate the data. Our main purpose is to make a selection from the available features per field. Eigenvalue or principal component analysis can be used to reduce the dataset into a set of uncorrelated features. This is done by a dataprojection on two or more Eigen vectors, which are determined from the covariance matrix of the dataset.

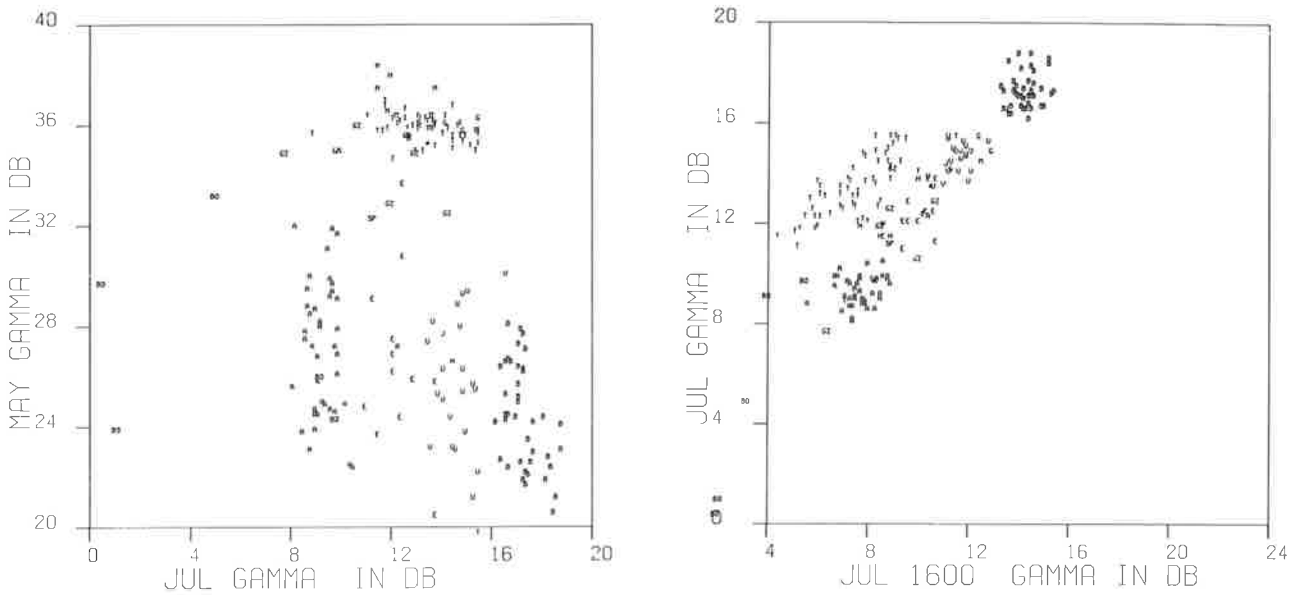

Figure 6. Feature space plots of May vs July and the 2 July-features (low and high altitude).

An evaluation of the dataset using this method showed that the first two eigen vectors contained 91 % of the total variance, which means that the other four eigen vectors may be deleted. The first eigen vector is mainly determined from the April - and May-features, whereas the second eigen vector is in fact a combination of the two July-features, so the two flights at different altitudes.

Since the datasets from April and May are highly correlated (correlation coefficient 0.91), the dataset of May was chosen as before and furthermore we selected the two July-features. Figure 6 shows feature space plots for May versus July and for the 2 July features. A cross reference of the labels used in this and other figures can be found in Table 1. In both plots clusters of croptypes can be distinguished. A projection on one of the axes makes the classes inseparable, except for the wheat in May of course and the sugarbeets in July. The combination of the two July features means that we deal here with angular dependences to obtain discrimination. The short time interval between these two measurements more or less guarantees that the differences are only caused by the change in incidence angle. Therefore the clusters are rather small. Even the winterwheat seems to be separable in this plot, but since this can be done in May, no further attention is paid to it. To reduce the dataset, we now introduce a linear combination determined as the first eigenvector of the two July features, to optimise the separability of the crops.

croptype	label	label
potatoes	A	1
sugarbeet	B	2
winterwheat	T	3
peas	E	4
onions	U	5
oats	H	6
winterbarley	GR	7
beans	BO	8
grass seed	GZ	9
spinach	SP	10

Table 1: legend to plotlabels

Figure 7 shows the plot of May versus the combination of the July features. Figure 8 shows a histogram of the July data projected on the new axis. Winterwheat fields are excluded in this histogram. The peaks are from left to right potatoe, peas, onion and sugarbeet. The classes can be separated with the parametric Bayes classifier for normal distributions.

A test of the designed classifier on the same data as used for the design, produced a very high classification result, which is not surprising. However since we have no other data available, it is difficult to test the classification algorithm.

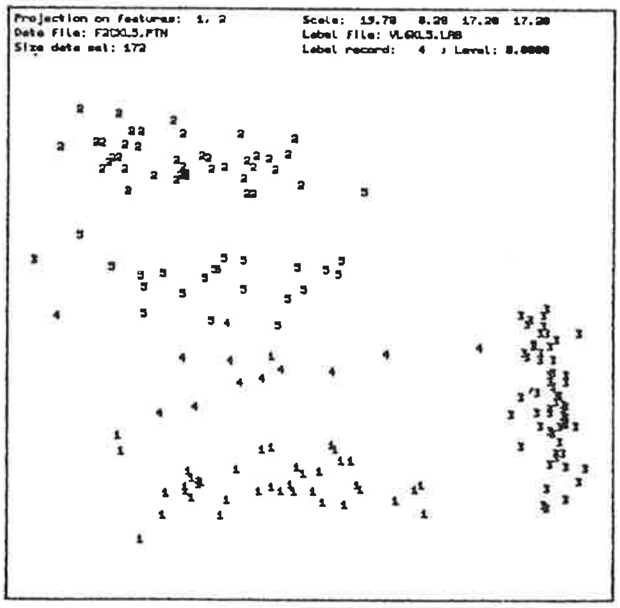

Figure 7. Plot of May versus the projection feature (linear combination of the 2 July features)

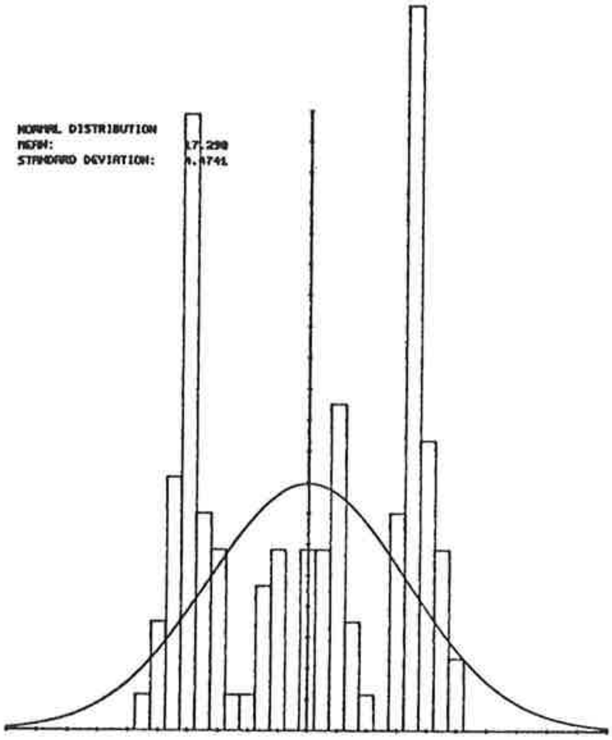

Figure 8. Histogram of the projection feature. Peaks are (left to right) potatoe, peas, onion and sugarbeet.

		CLASSIFIER LABEL							
		1	2	3	4	5	6	7	8
T	1	33		1	1				
R	2		36						
U	3			53					
E	4	1		1	5	1			
	5	2			1	11			
L	6			3			1		
A	7			3					
B	8	1							4
E	9			3	1	1			
L	10				1				

Table 2. Classification result after automatic field segmentation of the testarea (see table 1 for legend of labels).

To perform some sort of test, the data from fig. 2 was automatically segmented using a split and merge algorithm (Ref. 5) and then classified. This brings a little variation in the data, because the field boundaries now differ from the ones in the manual segmentation. Of course, this is only a small effect, therefore care should be taken in the interpretation of the classifier results. Table 2 shows these results. The first 5 classes were used for optimizing the design of the classifier. Classes 6 - 8 represent a very small amount of data and cannot be considered to be representative. Class 8 (beans) is not planted until July, so in July these fields are still almost bare, and therefore easy to recognize (see fig. 2). Classes 9 and 10 are not considered in the classifier and therefore identified as other croptypes.

3. TEXTURE ANALYSIS

Sofar we have only considered the use of field averaged backscatter coefficients as input to a classification algorithm. The reason is that the within field variations are believed to be caused by speckle, a phenomenon of coherent illumination. This leads to a multiplicative noise in the images, with a standard deviation of 5.6 dB for a 1 look image. The pixels in the SLAR images have 30 independent samples, which reduces the standard deviation to 1 dB and converts the negative exponential distribution of the individual measurements to a nearly normal distribution.

In some cases however, the inhomogeneities in the illuminated area may cause larger standard deviations and even produce textural effects. In such cases texture could be used as a feature for classification (Ref. 6). In theory it is even possible that the speckle statistics are influenced by the microstructure. It is for the optimization of the classifier of interest to know what contribution may be expected from statistical measures to the classification result. Therefore experiments were conducted on the dataset of figure 2 and on a SAR image (SAR 580, d.d. 3/7/81, X-band, HH polarization) of the same area.

First of all the standard deviation per field was calculated for the SLAR images of April and July (low altitude). Figure 9 shows the results. In April there is a difference in standard deviation between the bare fields and the vegetated fields. The standard deviation of the vegetated fields is in the order of 1 dB, which corresponds to our expectation on basis of the speckle. The bare fields however, have larger and more varying standard deviations, which is probably caused by variations in roughness and soil moisture of the top layer. For the vegetated fields the influence of the underlying soil on the backscatter is reduced by the attenuating effect of the vegetation. However, the difference in average backscatter between bare and vegetated fields is much larger than the difference in standard deviation. Therefore an important contribution to the classification is not expected from this feature in April.

In July, when all the fields, except beans, are fully covered, the standard deviation is always around 1dB, the expected value from the speckle noise. No contribution to the classification result can be expected in this case.

The principal component analysis, discussed earlier, confirmed these findings, when it was extended with the field standard deviations as features.

Although we find little or no contribution from the standard deviation to the classification, this does not necessarily mean that there is no texture. One needs higher order statistics to investigate this. An often used method to measure texture in images is based on the Gray Level Co-Occurence Matrix (GLCO or GLCM, Ref. 2), which provides a sensitive means of measuring small scale textures in images.

The GLCO is a matrix of relative frequencies P_{ij} with which 2 neighboring resolution cells separated by a distance $\vec{d}$ occur on the image, one with gray level i, the other with gray level j. Such a matrix can be produced by counting all the gray level pairs i,j with the specified distance $\vec{d}$ between them.

From the GLCO several textural measures can be calculated (Refs. 2, 7). One of them, which is used here, is the correlation measure:

$$\text{GLCO-CORR} \quad \sum_{i=1}^{M} \sum_{j=1}^{M} \frac{i.j.P_{ij} - m^2}{s^2}, \text{ with}$$

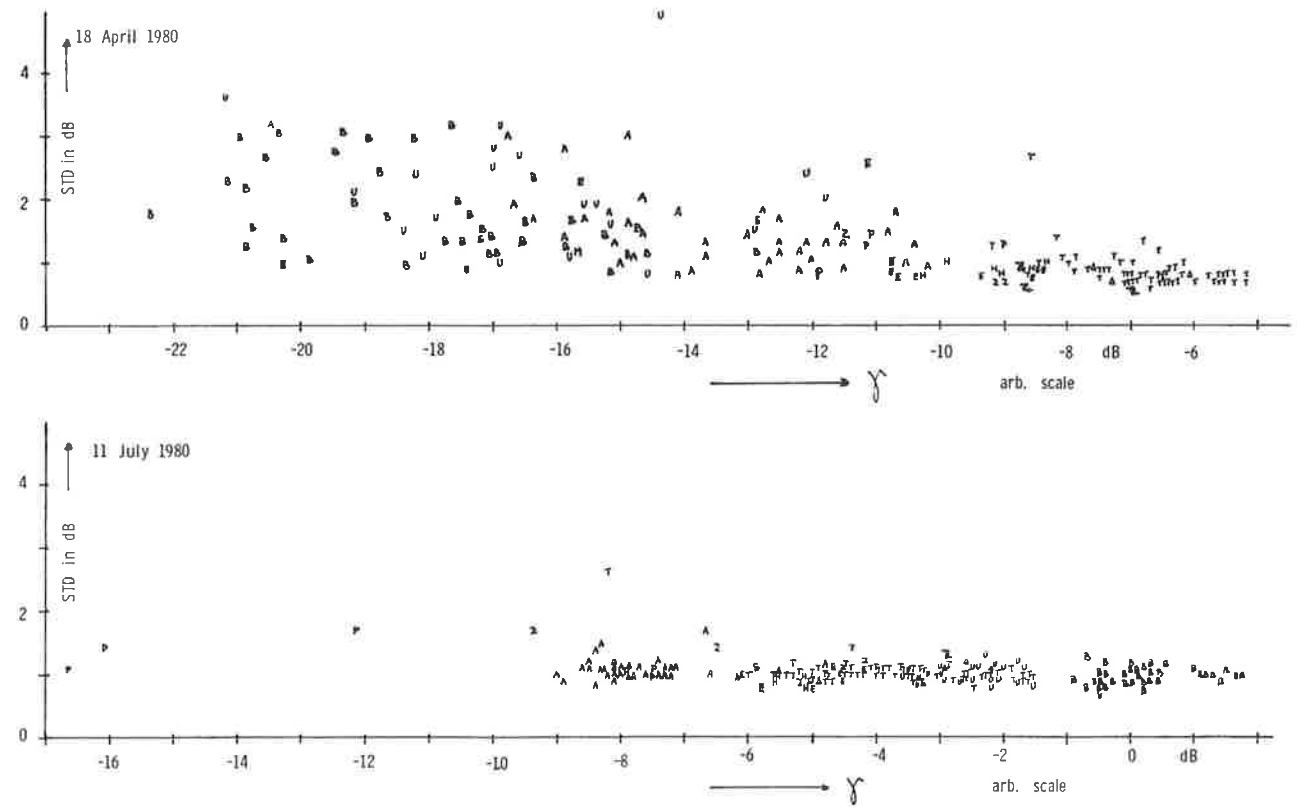

Figure 9. Within field standard deviation versus field-averaged backscatter coefficient for the SLAR flights of April and July (some labels differ from table 1: GZ→Z, WG→Δ, BO→P, SP→S).

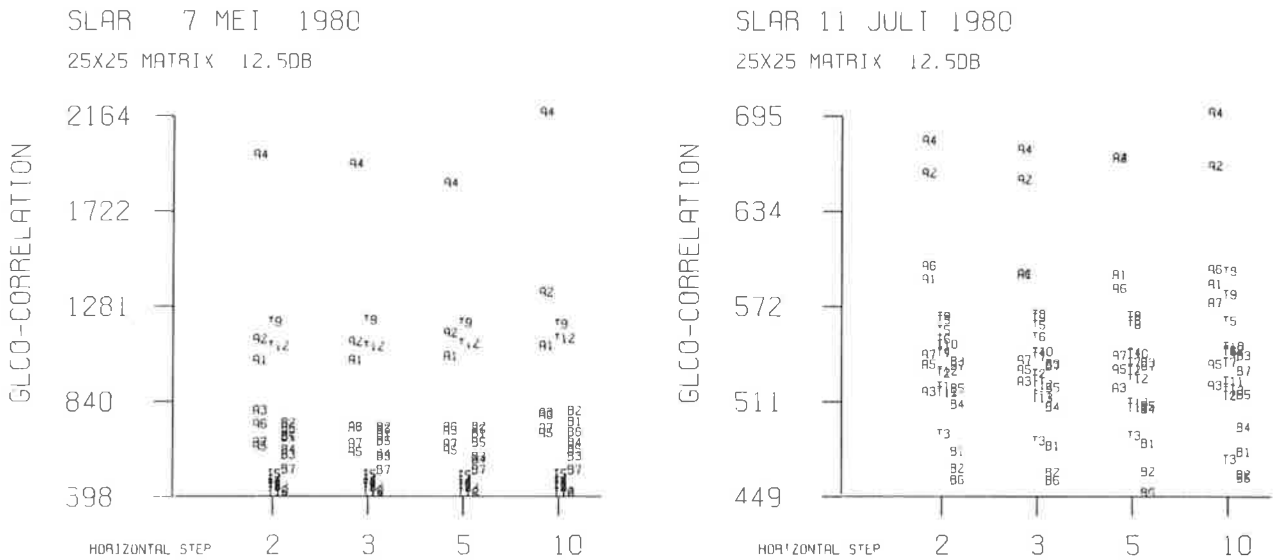

Figure 10. The GLCO-CORR measure plotted for varying horizontal pixel distance for the SLAR flights of May and July (low altitude). Three crop types are used: potatoe (A), winterwheat (T) and sugarbeet (B). They are plotted in separate columns to keep them recognizeable.

m = mean and s = standard deviation of the sums of the rows or columns. A second measure used here is the Gray Level Difference vector (GLD). This is in fact a histogram (relative frequencies) of gray level differences. It can be computed from the GLCO-matrix. The measure that is used here is:

$$\text{GLD-MEAN:} \quad \sum_{i=1}^{M} i.P_i$$

Figure 10 shows the computation of GLCO-CORR for the SLAR flights in May and July. In May the wheat fields are distinguishable, with a few exceptions whereas potatoe and sugarbeet are mixed. In July all the croptypes are mixed. This result is similar to

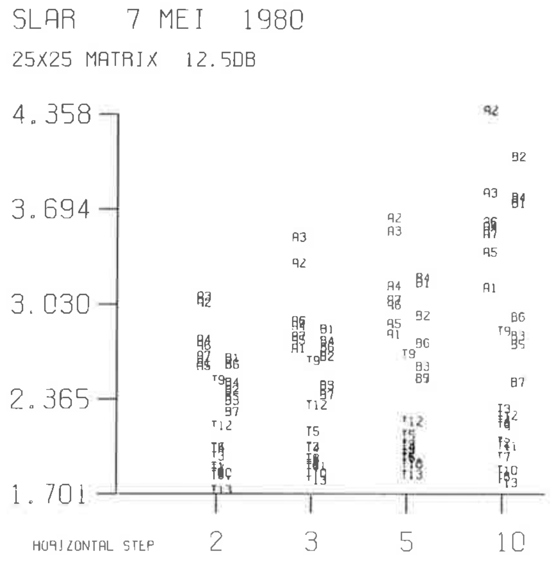

Figure 11. Plot of the GLD-Mean measure for May at varying pixel distances.

the result from the standard deviation. There is not much dependence on the distance between the pixels as it is varied from 2 to 10 pixels.

Figure 11 shows the GLD-MEAN for the SLAR flight of May and calculated for the same horizontal distances as before. The total range of the measure now increases with the pixel distance. The separability seems to be a little better than for GLCO-CORR, but once again hardly any extra information is added, if compared with the field averaged backscatter data.

Other textural measures based on the GLCO and the GLD were tested as well, but no significant extra information could be derived, also not if these measures were plotted in feature space plots. The conclusion based on this information must be, that for agricultural fields texture does not play an important role in these X-band SLAR images.

The growing interest in texture stimulated us to do some calculations on a SAR image which was taken in the same area, but at a different time (July 3, 1981). It is a SAR 580 image, X-band, with horizontal polarization. The pixelspacing in this image is 3 m, whereas the SLAR image had 15 m spacing between pixels. The increased resolution should in principle enable a better expression of smaller scale texture. On the other hand the speckle in this 4 look SAR image is higher than in the SLAR image, which is a 30 look image. Figure 12 shows a plot of the GLCO-CORR measure for the SAR 580 image, both with horizontal and vertical step. The plots look very similar, with no separation of any of the 3 crop types.

After having completed the first plot, the idea arose that field A4 (potatoe) perhaps had a different row direction, compared to the other potatoe fields. However, since the vertical and horizontal steps show the same result, this is not likely. The row direction in these fields is not known to us, but is probably parallel to the horizontal or vertical field boundaries (see fig. 1-3), which corresponds with the horizontal and vertical steps taken for the GLCO.

As before the conclusion seems to be, that the radar images investigated, show no textural variations within the agricultural fields, that can be applied for crop identification.

4. CONCLUSIONS

In this paper a follow-on study into the possibilities of crop identification was presented. The goal was to optimize the classification result from a previous study by adding early season SLAR flights and by investigating the potential of small scale texture in agricultural fields.

A hierarchic classification procedure is proposed. The success of this classifier is based on the separability of winterwheat or rather wintercrops at low grazing angles (5^0 - 15^0) in the early growing season (April, May) and the ability to discriminate other crop types in the mid-season on basis of their angular dependence in the grazing angle range 5^0 - 35^0. Field averaged radar backscatter values are used.

The test of the classifier was performed on the

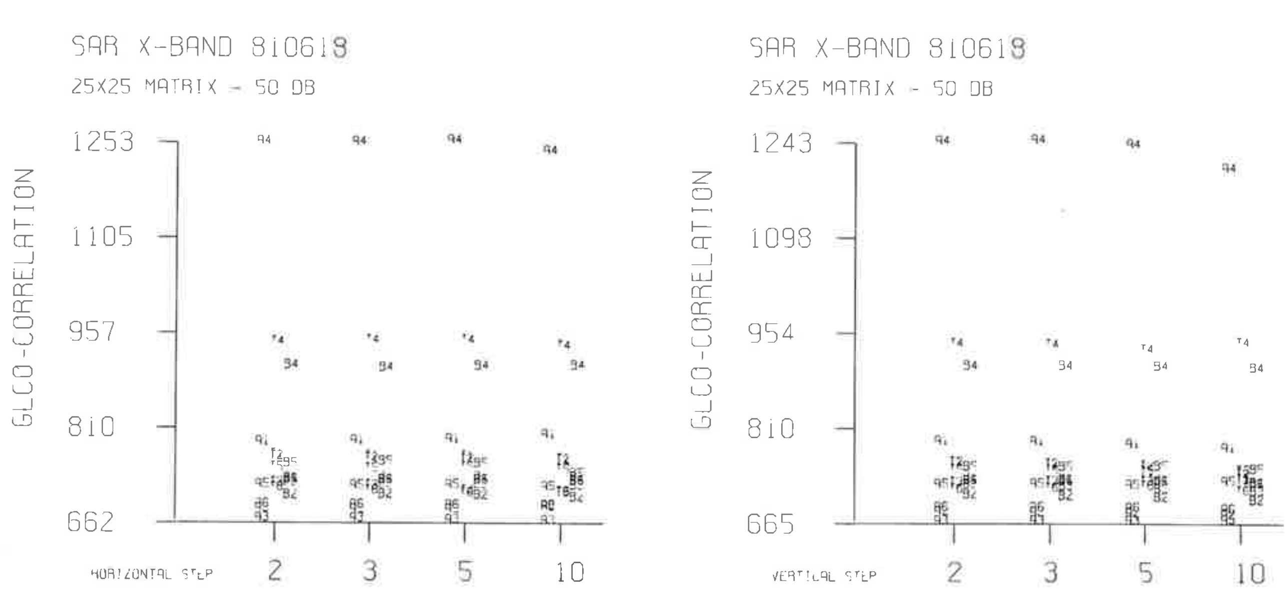

Figure 12. Plot of the GLCO-CORR measure for an X-band SAR 580 image at varying pixel distances, horizontal (left) and vertical.

same dataset as was used for the design of the classifier, although for the test the fields were segmented in a different way (automatic instead of manual). Care should be exercised in the interpretation of the test results, since the success percentages may be over estimated in this situation.

Further investigations should incorporate a test in ecologically different area's and area's with different and more varied crop distributions. Also the use of angular dependence should be further investigated. In The Netherlands a research project is running to cover these subjects.

The use of features other than the average radar backscatter, i.e. the standard deviation and GLCO textural measures, has sofar not shown to provide a significant contribution in crop classification. Although it is in theory not impossible, that small scale texture (even if it is smaller than the resolution of the radar) in agricultural fields is imaged by the radar, no sign of it was found in SLAR images and a SAR 580 image. If subresolution structures like row direction, plant distance, etc. influence the speckle statistics in an image, then this could perhaps be better judged from the raw SLAR data, where no averaging of single measurements has taken place. This was not investigated sofar.

5. ACKNOWLEDGEMENT

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