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A Field Mapping System to Distinguish Clover Stocks from Grass Thicket using a Texture Analysis Method

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Abstract

A machine-vision method applicable to precision farming for environmental friendly agriculture is proposed which distinguish which of clover and gramineous weeds is dominant, within a section of 30cm square. Pictures of vegetated ground are treated as random textures and micro-shape based feature extraction method is applied. As many as 98are correctly classified.

1 Introduction

In researches of precision farming, massive data on vegetation in widespread field is to be collected non-destructively during several seasons to analyze ecological dynamics of competing or symbiotic plants. Tedious and time-consuming manipulation would be required to summarize those data, say, to plot dominant groundcover plants on a field-map, by hands. One of such researches requiring spatio-temporal data acquisition is on going in which clover is introduced to suppress growth of gramineous weeds ecologically. We are developing a machine-vision method to distinguish which of clover and weeds is dominant in each small section. In this paper, we propose an automatic field-mapping system, which generates distinction results of the method on a map of a farm to be measured. Only if pictures of field is taken continuously by a camera carried by a farm tractor, a domain map of large field will be drawn automatically.

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2 Shape-Pass Filter

We treat a picture of stock of clover or weeds as a random texture and apply a general-purpose texture analysis method proposed in [1][2] by us and modified to be optimal for this purpose. In our previous method a texture is interpreted as a collection of tiny elementary shapes and identified by figures of portions of respective shapes contained in it. Nine micro-shape elements are tentatively assumed, which are named as black pepper, black roof, black line, black snake, cliff, white pepper, white roof, white line, and white snake (shown in Fig. 1). Peppers are isolated small area, roofs represent steep angular area, and lines as well as snakes are both long thin belt but the latter are curved, which are contrasted to background brightness. Cliff represents neighboring nearly equal black and white patches. In new version sizes of micro-shapes are taken into account for species discrimination reflecting the difference of average leaf sizes of both plants.

A bank of nonlinear filters for nine of micro-shapes by several sizes will be synthesized as a feature extractor since linear filters can never be sensitive to a specific shape in which phase relationships of harmonics are essential. Although a matched filter detects a shape as its output peak, its r.m.s. output is governed only by input power spectrum or second-order statistics. Each unit filter is designed following the rule of "programmic filter" which we proposed previously, which allows continuously gray-leveled inputs and copes with bias or

Figure 1: Micro-shape elements of textures (Black-Roof, Black-Line, Black-Snake, Black-Pepper, Cliff)

gain changes similarly to linear ones, but may contain logical operations as well as metric ones. Filter functions for nine micro-shapes are essentially the same as shown in [1][2].

3 Sample Images

Preliminary experimental pictures of groundcover plants are taken by a 35mm camera with 50mm lens held as high as 2m and inclined slightly to exclude legs of the ladder, and digitized into 1900 by 1350 pixels. 15 pictures of clover and 26 of grass are collected in wild field to constitute a training set, and 46 of mixtures are taken as test samples.

Before fixing filter sizes, optimal magnification of pictures is investigated. Training pictures are reduced into various magnifications of logarithmic steps up to 7original size and applied to a 11×11 programmic filter which is sensitive to the variance of brightness within the filter size followed by a programmic nonlinear smoother Where the brightness deviates, brighter or darker pixels may constitute an area of some shape. Table 1 shows a number of samples having maximally potential features on each magnifications. For clover photographs 18outputs, while 7is adopted for both and filter sizes are to be 5×5, 7×7, 11×11, 15×15, and 21×21 to range over the maxima of both. Thus the filter bank is constituted by 45 filters, that is, 9 for micro-shapes by 5 for sizes. The training pictures are shown as Fig. 2.

Table 1: Number of samples having maximally potential features vs. magnification.

reduction	clover	weed	total
7	1	15	16
9	0	2	2
13	3	5	8
18	6	3	9
26	5	1	6
37, 52 and 74	0	0	0
total	15	26	41

In classification process output pictures from 45 respective unit filters are divided into 16 sections.

4 Discriminant Analysis

Closer inspection of feature elements revealed that black line, white line and white snake over all filter sizes characterize gramineous weeds, while black roof, black roof and black snake are typical for clover pictures independently of sizes. On the other hand, small both black and white peppers as well as large cliff are favorable for grass, while large peppers and small cliff are often encountered in clover pictures.

Those results could be explained schematically by Fig. 3. Lines are naturally characteristic to monocotyledonous grass, but frequency of occurrence of micro-shapes are probabilistic. As shown in the figure for example small black roofs appear in both, but in clover pictures more frequently.

However, the above-mentioned tendency is only qualitative. In an actual image, a distribution of the feature is probabilistic, and an appearance frequency of micro-shapes swings widely in each sample. It is necessary to select effective features from all types of micro-shape by a discriminant analysis.

Magnitudes of 45 root-mean-squared outputs constitute the raw feature vectors for respective sections. Although intra-class covariance of clover sections and glass sections is not the same, linear discriminant function is adopted since introduction of Mahalanobis distance decreased error rate very slightly. 20 feature elements among 45 are selected to attain 97.9training sections, that is, 16×15 clover sections plus 16×26 grass sections.

As previously described, in classification process, output pictures from 45 unit filters are divided into 16 sections. Similarly, the discriminate analysis was done to images that were divided into 4 or 64. The distinction rate changed as shown in Figure 4 as a result. The classification error rate increases rapidly though analyzing by dividing into smaller sections can express a state of a farmland in detail. Then, we decided to use the image divided into 16 sections, each of which contains 225×153 pixels which corresponds to 38×25 cm area on the ground.

Table 2 shows the discriminant function obtained as a result of the discriminant analysis. Selected

Figure 2: Training pictures (upper: clover, lower: weed)

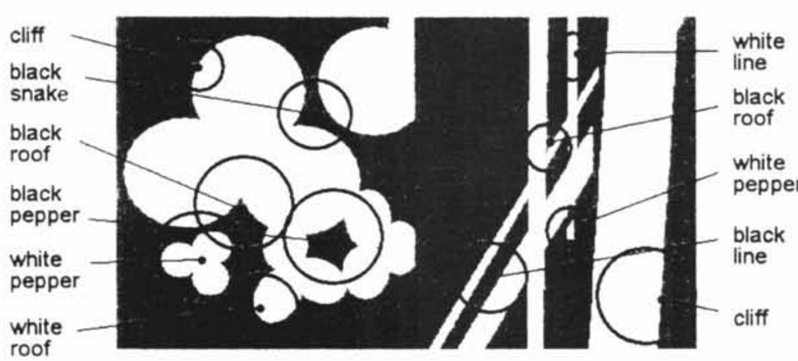

Figure 3: A schematic model of occurrence of micro-shapes in clover and grass pictures

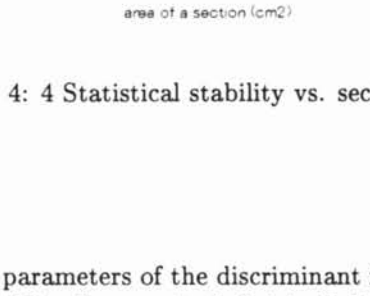

Figure 4: 4 Statistical stability vs. section size

features, parameters of the discriminant function to them, and F values are included in Table 2. Moreover, features that a sign of the parameter are opposite to the content of fig. 3 are shown in the column of the consistency by × mark. It is thought that this works complementary with other features.

5 Experiment

Among 432 sample sections from 27 test pictures of mixed vegetation of clover and grasses, machine classification of 386 samples coincided human judgement. 43 of rest 46 are very critical ones containing a border of both plants in a section. 3 were apparently erroneous. Typical classification result is shown in Fig. 5.

When both of a clover and weed exist together in one grid, unexpected micro-shapes are generated by overlapping of both. This method distinguishes according to an amount of the micro-shapes in the section. Therefore, if this amount of the feature does not become the proportional distribution of the area of both plants, the misjudgments is caused.

However, it is shown that a ratio where such vagueness are caused is about 10confirmed to be able to examine a distribution of colonies by using this method at intervals of almost 30 cm.

In an actual measurement, we took pictures of the field are taken continuously by a video camera carried by a farm tractor which run a constant speed.

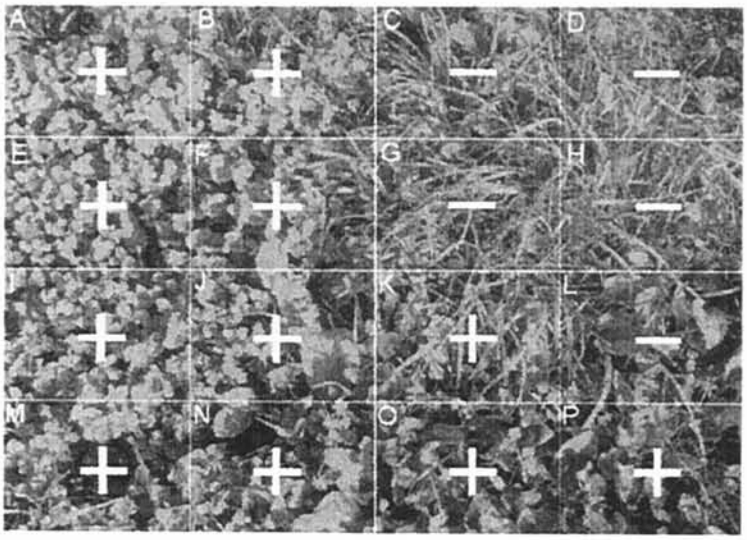

Figure 5: Result of classification + and - denotes clover and grass respectively

These pictures are recorded once on videotapes, and stored into a computer with a video capture device afterwards. Pictures by which grids of a target field are represented are obtained from among these pictures by selecting pictures at a constant rate calculated from the speed of the tractor. The method is applied to each grid by off-line after data is collected. As a result, domain maps of large field are able to be drawn automatically.

6 Conclusion

In conclusion, a novel method based on texture analysis to distinguish clover stocks from monocotyledonous grass thicket is proposed and successful results are obtained experimentally showing the applicability in precision farming.

References

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[2] H.TAMURA, O.ATODA: "A Bank of 'Shape-Pass' Nonlinear Filters Extracting Pictorial Features of Natural Textures", Trans. of the Institute of Electronics, Information and Communication Engineers, Vol.J82-D-II, No.12, pp.2260-2270,(1999) (in Japanese)

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Table 2: Parameters of a Clover-Grass discriminant function

Filter-size	Weight	F	Consistency
broof-7	0.35	24.38	
wroof-21	0.29	21.00	
wroof-7	0.30	20.73	
wroof-5	0.30	0.46	
wpepper-5	-0.30	18.32	
bsnake-5	0.41	15.23	
wline-21	0.39	13.11	
bpepper-21	0.07	12.07	
wline-5	-0.22	11.03	
wsnake-5	-0.45	11.03	
bsnake-11	0.10	9.52	
wsnake-7	-0.29	9.11	
bsnake-7	0.22	9.08	
cliff-11	-0.11	7.62	
broof-11	-0.18	6.70	×
wpepper-21	0.14	6.15	
cliff-5 0.10	5.20		
bline-5 -0.10	5.03		
wline-7 -0.14	3.99		
broof-21	0.07	2.97	
cliff-7	-0.09	2.64	×
wpepper-15	-0.10	2.03	×
Const.	-13.97		