EXTRACTION OF WHEAT EARS WITH STATISTICAL METHODS BASED ON TEXTURE ANALYSIS

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Abstract: In the agronomic domain, the simplification of crop counting is a very important and fastidious step for technical institutes such as Arvalis[1], which has then proposed us to use image processing to detect the number of wheat ears in images acquired directly in a field. Texture image segmentation techniques based on feature extraction by first and higher order statistical methods have been developped for unsupervised pixel classification. The K-Means algorithm is implemented before the choice of a threshold to highlight the ears. Three methods have been tested with very heterogeneous results, except the run length technique for which the results are closed to the visual counting with an average error of 6%. Although the evaluation of the quality of the detection is visually done, automatic evaluation algorithms are currently implementing. Moreover, other statistical methods of higher order must be implemented in the future jointly with methods based on spatio-frequential transforms and specific filtering.

1 INTRODUCTION

Manual wheat ear counting for yield prediction requires high labor cost in addition to the time that needs to be achieved. Recently many works have been carried out on the agriculture domain (remote sensing, weed detection…) by using image processing techniques, but little research has been done on wheat ear detection and counting (Germain et al., 1995), which are however two important steps for yield evaluation or prediction. Since Arvalis wants to replace the manual counting by an automatic one, a feasibility study on the use of image processing techniques has been proposed in 2004 (Guérin et al., 2005). The way explored in this study combines information jointly provided by texture and colour analysis, which allow to represent each image in a color-texture hybrid space. This study showed that the use of image processing techniques directly in the field is an interesting solution, but, although the results obtained are satisfactory, the different algorithms must be validated on numerous images, and contain some disadvantages mainly in detection phase due to no recurrent hybrid space. Consequently Arvalis decided to continue this project with a first objective based on the improvement of the detection step. It appears that the combination of texture and color analysis is not clearly evident for our application. Particularly, the color and the shape of ears (figure 1) depend on the wheat growth stage and the illumination conditions.

Figure 1: Wheat images acquired in field at different growth stages (from flowering (April-top left) to harvest (July-bottom)).

[1] French plant and feed-grain research institute.

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In order to avoid this problem, we decided to focus our approach on the development of texture analysis before associating the color information because texture is very rich in information.

2 IN-FIELD IMAGE ACQUISITION SYSTEM

The acquisition system must allow to take photographs at different wheat growth stages with a good resolution. We use a Canon digital camera (5 Mpixels) which takes images on an 0.5*0.5 m² homogeneous test area of wheat delimited by a black matt frame as shown in figure 2. The digital CCD camera is controlled by a PC laptop and is located vertically above the field of view at a height of 0.93 m.

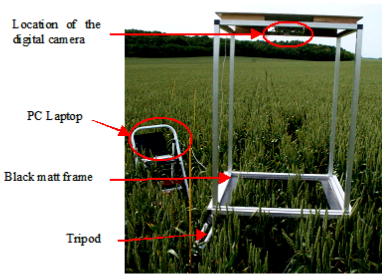

Figure 2: In Field image acquisition system.

Taking photographs directly in the field needs to control the illumination of the scene. Because we take images under different lighting conditions, due to variable cloud cover and solar illumination, we use some screen protection system (not shown in the figure 2) to limit the light in the area of study.

3 WHEAT EAR EXTRACTION BY PIXEL CLASSIFICATION

All the acquired images contain three important classes: wheat ears, stems and leaves, and soil. Their extraction can be done using texture and/or color image analysis techniques. The current approach proposed in this paper is only based on texture analysis techniques because texture and color seem to be independent phenomena that should be treated separately (Mäenpää and Pietikäinen, 2004) (even if some recent works (Foucherot et al., 2004) have shown that the color of an image can slightly modify the texture) and the information obtained with texture analysis are available for each wheat growth stage.

3.1 Statistical Methods of Feature Extraction

The non-periodicity of the position of the ears in each image conducted us to use statistical methods for feature extraction. These methods study the interaction between a pixel and its neighbours in term of intensity. In literature, many methods are proposed but none of them is generally applicable to all kinds of images and different algorithms are not equally suitable for a particular application. This can be proved in figure 4 in which we tested the method based on Cross-Diagonal Texture Matrix, defined by Al-Janobi in 2001 and the method based on grey level differences defined by Weska et al. in 1976 to discriminate Brodatz textures (Brodatz, 1966) and wheat ears.

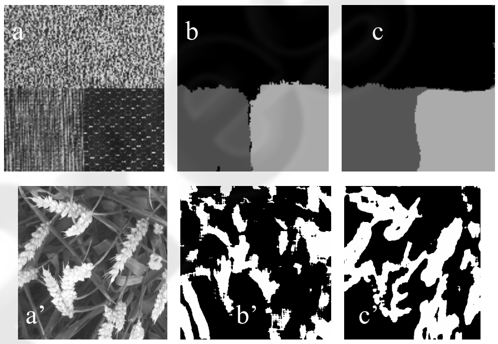

Figure 3: Results of classification with cross-diagonal texture matrix and grey level differences. (a) and (a'): test images. (b) and (b'): segmentation with cross-diagonal. (c) and (c'): segmentation with grey level differences.

The two previous methods do not allow a well recognition of the wheat ears, which can be due to the aspect of the textures (local grey scale variations), texture orientation, non-homogeneous objects to detect, … For these different reasons, we decided to study other statistical methods of first and higher-order. The first order method implemented is based on the computation of a mono-dimensional histogram of the intensity (Pratt, 1991) from which 7 features are extracted: Mean, Variance, Energy, Entropy, Contrast, Skewness, Kurtosis. Nevertheless, this technique does not consider the correlation between pixels in the processing. This drawback is resolved by the study of a bi-dimensional histogram based on the computation of the co-occurrence matrix defined by Haralick et al. in 1973. From this matrix, we extract some Haralick features that allow a better texture discrimination (Conners and Harlow, 1980) and also three others features (cluster shade, cluster prominence and diagonal moment) (Unser, 1986):

$$Dmoment = \sum_{i=0}^{N\max-1}\sum_{j=0}^{N\max-1}\left(\frac{1}{2}*|i-j|*P(i,j,d,\theta)\right)^{\frac{1}{2}}$$

$$CShade = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i+j-2*moy)^3 P(i,j,d,\theta)$$

$$CProminance = \sum_{i=0}^{N_{\max}-1}\sum_{j=0}^{N_{\max}-1}(i+j-2*moy)^4 P(i,j,d,\theta)$$

where (i,j) represents the grey scale of the current pixel, P(i,j) designs the probability to find the grey scale i with neighbour j in the considered region, and $N_{\max}$ is the maximum intensity in this region.

Despite the good results obtained by this method, it depends on the choice of direction and need an important computing time although it can be reduced by decreasing the quantification to the detriment of the loss of information. For a better description of the texture, statistical methods of higher-order seem to be more suitable (according to the obtained results). One of the most popular methods is the run length matrix defined by Galloway in 1975. This method is based on the determination of the runs of grey levels that are present in the image or an area of the image. To summarize the information brought by run length, we define a matrix in which we can extract 11 features among which the Short and Long Run Emphasis, the Grey Level Distribution, the Run Length Distribution and the Run Percentage.

3.2 Unsupervised Pixel Classification by K-Means Algorithm

In literature, a great number of classification algorithms based on distance measurement, K-nearest-neighbours, Support Vector Machine (Burges, 1998), … have been developped. The K-Means algorithm is one of the most used in several works due to its simplicity of implementation and the good results that it provides in texture classification. First, the features are normalised and the class centres are randomly initialised. Then each pixel k is assigned to a class C_i if the Euclidian distance between its attributes and the centre of the class is minimal. Finally, the centres are updated by calculating the mean of each attribute given by the equation (1) and the process is iterated until stabilisation fixed by a criteria given by the formula (2):

$$\mu_k = \frac{1}{n_k}\sum_{z\in C_k} t_{i,j} \qquad (1)$$

$$crt = \sum_{i=0}^{Nc-1}\sum_{j=0}^{Np-1} Uij - U_1 ij \rightarrow 0 \qquad (2)$$

Where:

μ_k : centre of gravity of the class C_k,

$t_{i,j}$: attribute j of considered pixel i,

n_k: number of pixels at the class C_k.

Uij : class centre updated at the step k-1,

U_1ij: new class centre updated at the step k,

Nc: number of classes considered in the processing,

Np: number of parameters.

Other algorithms of classification have also been applied in agriculture, such as neural network, which are used to evaluate, for instance, the quality of apple surface combined with knn and Bayesian classification (Kavdir and Guyer, 2004). However our application depends of a lot of parameters, which give us numerous different images, and the learning seems to be quite difficult.

3.3 Evaluation of the Detection and Segmentation

Although numerous segmentation algorithms have been developed these last years, none of them can be universally used. To evaluate these methods the visual evaluation is always used as the reference method. However, evaluation criteria have been defined in literature and can be divided into categories: with or without ground truth. According to Laurent et al. in 2003, the most suitable criteria for uniform or less textured images are those defined by Zeboudj in 1988 and Borsotti et al. in 1998, whereas Rosenberger criteria (Rosenberger, 1999) is more suitable for texture images.

Here the evaluation of the different results is visually done but some unsupervised criteria of detection evaluation are currently implemented. Moreover, results obtained from agronomists on numerous images took at different wheat growth stages and for different illumination conditions will be compared in a few days with automatic counting.

4 RESULTS AND DISCUSSION

To put across our study, some in-field images have been tested by the different statistical techniques implemented. The figure 4 shows the results of the wheat ear detection obtained for one image among the in-field acquired images done by Arvalis.

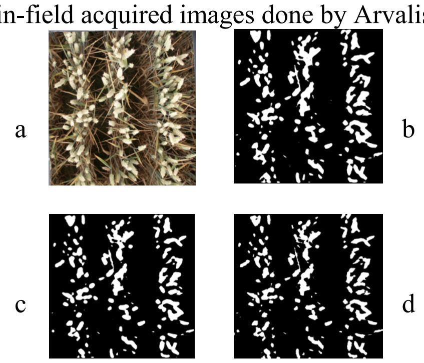

Figure 4: Results of segmentation obtained by the different techniques implemented for a whole image: (a) Test image. (b) with 1st order statistic. (c) with co-occurrence matrix. (d) with run length.

The previous results seem to be good, but visual evaluation is too long to be done on numerous images.

Taking into account the different tests carried out until now, it appears in this case that the three methods give good results, even if run length method reproduces nearly the real shape of the ears as it is shown in the figure 5.

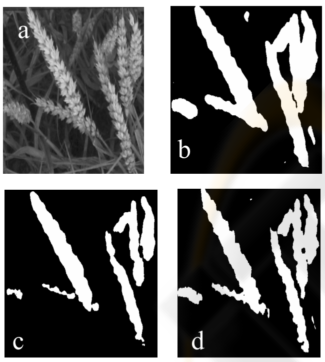

Figure 5: Wheat ear detection with the three different methods implemented for a part of an image. (a) Test image. (b) with 1st order statistic. (c) with co-occurrence matrix. (d) with run length.

These last results are very instructive because the second step of our project will be focused on the counting of the number of grains per wheat ears, and it appears that the Run Length method could be interesting. Although the results are given for a few number of images, the table 1 confirms that run length method is the most appropriated method for our application, according to the other methods.

Table 1: Detection of wheat ears by the different methods.

	Image 1	**Image 2**	**Image 3**	**Image 4**
Visual detection ('true' value in bold)	**184**	**179**	**128**	**150**
With 1st order statistics	190	156	116	134
With co-occurrence matrix	174	139	119	131
With run length	*182*	*159*	*123*	*141*

The evaluation of the detection quality is actually done visually and by comparison of the results of automatic counting with those done manually by Arvalis. A comparison will be provided soon, jointly with other results tied to a visual evaluation done by agronomist experts.

Finally, in order to test a lot of images in one step, wheat ear simulated images will be interesting and constitutes another step of our application. These images will be able to accurately represent the different wheat growth stages, the different illumination conditions, the different shapes, …

4 CONCLUSION

In this paper, we presented automatic wheat ear detection based on textural feature extraction. Three statistical methods of first and higher-order have been used in an unsupervised pixel classification algorithm based on K-means. The results of the detection with the Run Length method are quite close to visual detection but all the methods need to be validated on numerous images, took in different lighting and wheather conditions, and must be evaluated by the quality of the detection they allow.

As previously mentionned, this work is also part of a more global project to facilitate the countings for the agronomist technicians, but also to give in final an evaluation of the wheat yield before the harvest. In terms of image acquisition, an autonomous mobile robot used for different applications is under construction, simultaneaoulsy with the development of other texture analysis methods based on orthogonal transforms and specific filtering.

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