WHEAT GROWTH STAGES DISCRIMINATION USING GENERALIZED FOURIER DESCRIPTORS IN PATTERN RECOGNITION CONTEXT

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ABSTRACT

In the agronomic domain, the use of colour image acquisition, independently of remote sensing, is envisaged since several years generally to better define the appropriated periods for the spraying or fertilizer input. The use of a specific image acquisition system coupled to reliable image processing should allow an acceleration of the works, a lower penibility and a reduction of the bias of the measurement according to the operator, or a better spatial sampling due to the rapidity of the image acquisition.

Nevertheless, the use of natural images involves some difficulties tied to outdoor conditions (lighting variations) and object complexity (several planes for leaf areas, high contrast, scale variations, growth staging of the crop …).
In the context of Precision Agriculture, and based on previous works that focused on shape detection for wheat counting, this article explores the capacity and the performance of the combination of Generalized Fourier Descriptors feature extraction (GFD), projection methods and Support Vector Machine (SVM) classification method applied to wheat growth stages determination. Our main objective will be after to propose to the farmers a decision-aid tool for fertilizer input control and a model for the image feature evolution. The performances are evaluated with a 10-fold cross-validation process and in term of classification error rate. The experiments are carried out with a sample of wheat images acquired at different growth stages and for 3 years of harvest. Results show that the methodological combination of GFD with Linear Discriminant Analysis (LDA) and SVM classification returns pertinent results, with errors of classification under 1%, compared to the 15% of errors for classical classifications. At this stage, it seems however that we should include an agronomic validation in order to propose more specific model to help farmers.

Keywords: Wheat growth stages estimation, Generalized Fourier Descriptors, Projection methods, Support Vector Machine.

CONTEXT AND PREVIOUS AGRONOMICAL WORKS

In the agronomic domain, the use of colour image acquisition, independently of the remote sensing context, is envisaged since several years in the context of precision agriculture. Particularly, technical or research organisms, such as INRA or Arvalis[1], have understood the interest to provide decision-aid tools for farmers, for instance to help us to better define the appropriated periods for the spraying or fertilizer input. The use of specific image acquisition system coupled to reliable image processing should allow an acceleration of the works, a lower penibility, a reduction of the bias of the measurement according to the operator or a better spatial sampling due to the rapidity of the image acquisition.

Nevertheless, the use of natural images involves some difficulties tied to outdoor conditions (lighting variations) and object complexity (the leaf area presents several planes, high contrast and lighting variations, scale variations, wheat growth stages ….). However, the associated treatments on this kind of images (color, texture, shape) are not evident compared to images acquired in laboratory conditions with controlled lighting.

Our research was then focused on the conception of a reliable image acquisition device and on the development of an invariant and robust image processing tool to answer to the following demands:

- evaluation of wheat yield

[1] Plant and Feed-grains research institute

- evaluation of plants lifted number
- determination of a fraction of leaf coverage
- global determination of the percentage of wheat diseases
- evaluation of the crop growth stage
- ...

The first works have been then to develop a simple image acquisition device (Figure 1), to avoid sunlight problems, and some specific algorithms to detect and count the number of wheat ears per m², first wheat yield component, and fastidious task manually done by agronomist technicians.

Figure 1. Simple image acquisition system.

Its principle relies on the use of a closed box inside which a controlled illumination based on power-leds (3W and 5W, figure 2) is mounted (Cointault et al., 2008).

Figure 2. The Power-leds used (left); their location (middle); one image took with the two Leds (right).

This image acquisition device is used to evaluate earlier the wheat yield which needs to determine:

- the number of wheat ear number per m²
- the number of grains per wheat ear
- the thousand corn weight.

A first feasibility study leads in our laboratory recently (Cointault et al., 2008) has shown that the combination of texture and color information allows to detect and count the number of wheat ears per m² with precision of less than 6% compared to manual counting. In parallel to the evaluation of the number of grains per ear, color image processing and acquisition could allow to evaluate the different wheat growth stages (figure 3) (or other crops).

For the first step of this current project, we only consider images with visible ears, limiting the number of growth stages which can be discriminated.

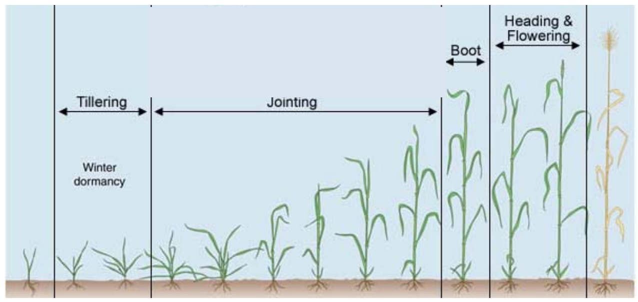

Figure 3. Growth staging of wheat from November (left) to July (right) (University of Illinois).

EVALUATION OF THE GROWTH STAGE OF THE CROP

The goal is then to study not only the ears but also all the image, in order to characterize the entire agronomic scene, by extracting a feature on the whole texture, to:

- help the farmers to do their fertilizer input (decision-aid tool)
- propose a model for the image feature evolution
- establish a predictive model based on the process of an image signal, which would characterize the crop.

To evaluate the wheat growth stage from an image, several approaches in image processing can be used, the most significant consisting to extract from an image a unique feature to sign the evolution stage. In the image acquired for our application (Figure 4), it clearly appears that a frequency signal represents a relevant potential.

Figure 4. Sample images from the youngest to the oldest class (from upper left to bottom right).

Spatio-frequency filtering methods have been thus investigated based on invariant feature. The aim is to extract only the useful signal from the image. In the literature, most currently used methods are based on Gabor filters (Arivazhagan et al., 2006), Markov field (Rellier et al., 2004), Wavelets (Kim and Kang, 2007) and more generally, on Fourier feature extraction. Within the existing methods, our choice is oriented on the Generalized Fourier Descriptors (GFD) for the following reasons:

- invariant for rotation, translation and reflexion
- commodity for implementation
- robustness

MATERIAL AND METHODS

Generalized Fourier Descriptors

We extract the feature parameters by using the Generalized Fourier Descriptors (GFD) (Smach et al., 2007) obtained from the gray level image. The GFD are defined as follows. Let f be a square summable function on the plane, and $\hat{f}$ its Fourier transform:

$$\hat{f}(\xi) = \int_{\mathbb{R}^2} f(x)\exp\left(-j\left\langle \xi \middle| x \right\rangle\right)dx. \qquad (1)$$

Where $\langle . | . \rangle$ is the scalar product in $\mathbb{R}^2$

If (λ, θ) are polar coordinates of the point ξ, we shall denote again $\hat{f}(\lambda, \theta)$ the Fourier transform of f at the point (λ, θ). Gauthier et *al*. (Gauthier et al., 1991) defined the mapping D_f from $\mathbb{R}_+$ into $\mathbb{R}_+$ by:

$$D_f(\lambda) = \int_0^{2\pi} \left| \hat{f}(\lambda, \theta) \right|^2 d\theta \qquad (2)$$

So, D_f is the feature vector which describes each grey level image and will be used as an input of the supervised classification method. Motion descriptors, calculated according to equation (2), have several properties useful for object recognition: they are translation, rotation and reflexion-invariant (Lemaître et al., 2007).

Classification method

Classification is a central problem of pattern recognition (Duda et al., 2001) and many approaches to solve it have been proposed such as connectionist approach (Bishop, 1995) or metrics based methods, k-nearest neighbours (k-nn) and kernel-based methods like Support Vector Machines (SVM) (Vapnik, 1998), to name the most common. In our experiments, we want to evaluate the

performance of the GFD to provide a robust and pertinent feature for the wheat growth estimation.
In this context we choose the SVM approach due to the good results obtain by this method in pattern recognition area and its robustness as it shown in (Smach et al., 2007; Cointault et al., 2008).
We have excluded the majority of neural networks methods due to the high variability of natural images; Variability which includes an infinite number of samples required for the learning step (wheat growth stages, pedo-climatic conditions, roughness, hydration state,…). In order to validate the classification performance and estimate the average error rate for each classification method, we performed 20 iterative experiments with a 10-fold cross validation procedure.

Dimensionality Reduction method

The GFD method provides features that are of great potential in pattern recognition (Smach et al., 2007). Unfortunately, these high dimensional features are however difficult to handle, the information is often redundant and highly correlated with one another. Moreover, data are also typically large, and the computational cost of elaborate data processing tasks may be prohibitive. Thus, to improve the classification performance it is well interesting to use Dimensionality Reduction (DR) technique in order to transform high-dimensional data into a meaningful representation of reduced dimensionality (Lee and Verleysen, 2007). For this experiment and based on previous work (Cointault et al., 2008), we choose the well known Linear Discriminant Analysis (LDA) (Duda et al., 2001) in order to reduce the dimensionality and also increase the separability and compacity of clusters for an optimization of the classification. Before proceeding to DR, we need to estimate the intrinsic dimensionality.

Estimating intrinsic dimensionality

Let $\mathbf{X} = (\mathbf{x}_1, ..., \mathbf{x}_n)^T$ be the $n \times m$ data matrix. The number n represents the number of image samples contained in each growth stage class dataset, and m the dimension of the vector $\mathbf{x}_i$, which is the vector corresponding to the discrete computing of the D_f (from eq. (2)). We have in our case n=346 and m= 255. Ideally, the reduced representation has a dimensionality that corresponds to the intrinsic dimensionality of the data. One of our working hypotheses is that, though data points (all image) are points in $\mathbb{R}^m$, there exists a p-dimensional manifold $\mathrm{M} = (\mathbf{y}_1, ..., \mathbf{y}_n)^T$ that can satisfyingly approximate the space spanned by the data points. The meaning of "satisfyingly" depends on the dimensionality reduction technique that is used. The so-called intrinsic dimension (ID) of X in $\mathbb{R}^m$ is the lowest possible value of p $(p<m)$ for which the approximation of X by M is reasonable. In order to estimate the ID of our two datasets, we estimate the residual variance with Isomap method (Tenenbaum et al., 2000) for all dimensionality reduced data. Using this method, we estimated and fixed the

intrinsic dimensionality of our dataset at ***p=5*** which corresponds to the dimensionality for the minimum value of residual variance (Figure 5).

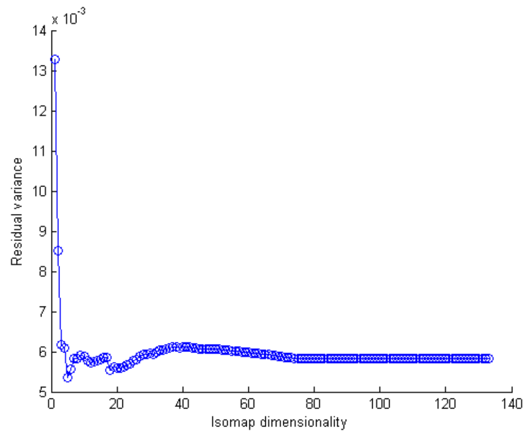

Figure 5. Estimation of the intrinsic dimensionality by residual variance estimation.

RESULTS AND DISCUSSION

346 image samples have been acquired for the experiments (cf. Figure 4) and labelled into 4 classes representing the different growth stages from the youngest to the oldest (from May to July). Each class contains images from 3 different year's acquisition sampling with illuminant, scale and location variability.

In order to validate our model, a 3-steps protocol (3 experiments) has been applied and a final comparison of the all error rate classification obtained in each step using cross-validation has been carried out.

Step 1: classification of raw GFD data, without any selection.

Step 2: classification after deletion of outliers which have been observed during the first step using PCA on raw GFD data.

Step 3: application of LDA method with the remaining signatures coming from the second step

Table 1. Classification results for the three experiments.

	Step 1	**Step 2**	**Step 3**
Classification error rate (%)	15,6	9,53	0,82

Result analysis of the first step

The first experiment carried out on the all image dataset provides an encouraging result with 15% of error rate classification (Table 1). Unfortunately, some outliers appear due to the important illuminant and scale variability which increase the classification error rate.

In order to decrease the error rate and select the best condition for acquisition, we perform a principal component analysis (PCA) aiming at finding outliers sample (Figure 6)

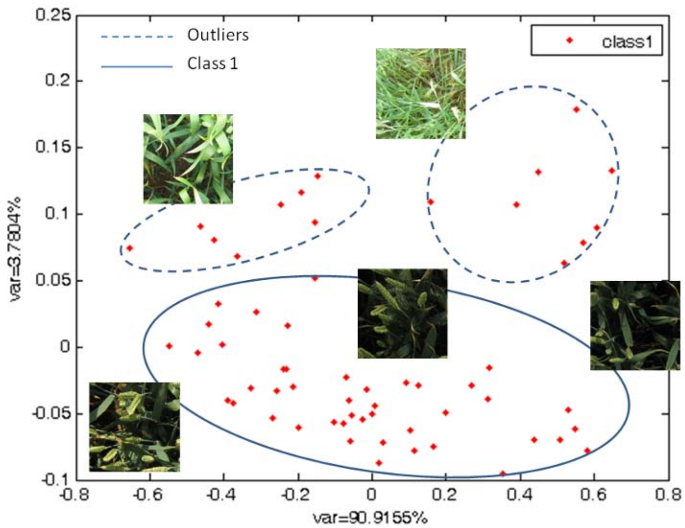

Figure 6. Outlier's detection with principal component analysis for the class 1.

According to the results obtained with PCA projection, we can define the optimum settings for the image acquisition system by cancelling the settings which provide outliers in PCA space. It appears that the outliers in PCA space correspond to over and under-exposed or blurred images with a high variation of focal distance compared to the most represented acquisition settings.

<u>Result analysis of the second step</u>

The second experiment carried out on the cleaned selected image dataset (sample without outlier's obtained by PCA) shows a 6% improvement of the classification error rate (9.53%). It confirms the importance of the constancy of acquisition and the pertinence of the use of a standard acquisition system (acquisition box, settings,...).

<u>Result analysis of the third step</u>

The third experiment is carried out with the same dataset used in step 2. We perform a Linear Discriminant Analysis in order to increase the separability and the compacity of the different classe's cluster which correspond to the different growth stages. The result shows that the error rate classification fall to 0.82%. It represents a significant improvement of the classification error rate which is illustrated by the LDA projection of the 4 growth stage clusters (Figure 7). We can show on this projection the complete separability of the 4 clusters and their high compacity.

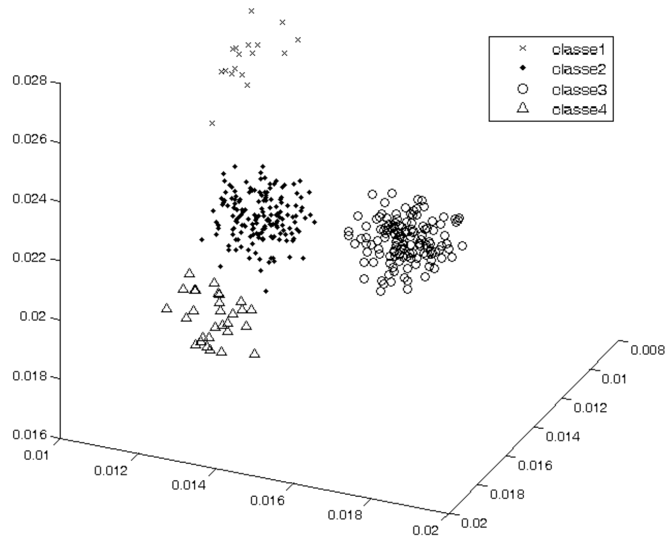

Figure 7. LDA projection of the 4 classes of GFD.

In the figure 7, the class 1 corresponds to the youngest wheat growth stage and the class 4 to the oldest. These results demonstrate that the LDA combined with SVM offer a useful tool for wheat growth stage estimation.

To avoid outliers, imaging acquisition system has to be improved especially for the control of the illumination and for the protection against solar lighting. Moreover, the focal length change is a parameter to take in consideration while discrete GFD could be slightly affected by scaling.

This research must be combined with agronomical models to propose to the farmers a more precise adaptation of their spraying according to landscape gathered data analyzed with our method. Moreover, our device could be used to detect the evolution of diseases on a crop in order to optimize the treatments.

However, we have to validate these results on several other classes or groups to increase our sampling. For example, it could be interesting to extend the image acquisition to the whole period of wheat development, that is to take images starting in October until the harvest.

CONCLUSION

In this paper, we recalled the first works done on the use of image processing in agronomy for the detection and counting of wheat, using images acquired in external conditions.

This goal close to be achieved has revealed the possibility of extending the use of pattern recognition techniques and frequency analysis to other applications, including the automatic determination of the wheat growth stage, aiming at creating a decision tool for farmers.

To achieve this goal, we developed an image processing protocol based on the powerful Generalized Fourier Descriptors which have interesting properties such as translation, rotation and reflexion invariants, combined with the SVM classification method. This combination provides relevant results. Moreover, we experimentally demonstrated that LDA method improves final classification performances.

For our application, we showed that the wheat growth stage can be determined by image processing taking the pattern recognition view point. These treatments allow us to eliminate over and under-exposed images and to conserve a range of illumination conditions for improvements of future image acquisition settings. Nevertheless, because the GFD method is not invariant in term of scale, the most important parameter to take into account for image acquisition is the focal length which must be the same for all the set of images. Moreover, we are currently testing our method for different sets of images took at various focal lengths, to propose the best focal distance to use.

At this stage, it seems that we should include an agronomic validation in order to propose more specific model to help farmers. With the help of agronomist, we need to improve this experiment with agronomical models

In the same context we have the perspective to take satellite or aerial images in order to test the feasibility of similar approach taking a more global view.

REFERENCES

Arivazhagan, S., Ganesan, L. and Priyal, S. P. (2006). "Texture classification using Gabor wavelets based rotation invariant features." Pattern Recognition Letters 27(16): 1976-1982.

Bishop, C. M. (1995). Neural Networks for Pattern Recognition, Oxford University Press.

Cointault, F., Guérin, D., Guillemin, J. P. and Chopinet, B. (2008). "In-Field Wheat ears Counting Using Color-Texture Image Analysis." New Zealand Journal of Crop and Horticultural Science 36: 117-130.

Cointault, F., Journaux, L., Miteran, J., Destain, M. F. and Tizon, X. (2008). Improvements of image processing for wheat ear counting. International Conference on Agricultural Engineering & Industry Exhibition (Ageng'08) Hersonissos, Crete - Greece.

Duda, R. O., Hart, P. E. and Stork, D. G. (2001). Pattern Classification (2nd Edition). New York, Wiley Interscience Publication.

Gauthier, J.-P., Bornard, G. and Silbermann, M. (1991). "Harmonic analysis on motion groups and their homogeneous spaces." IEEE Transactions on Systems, Man and Cybernetics 21(1): 159-172

Kim, S. C. and Kang, T. J. (2007). "Texture classification and segmentation using wavelet packet frame and Gaussian mixture model." Pattern Recognition 40(4): 1207-1221.

Lee, J. A. and Verleysen, M. (2007). Nonlinear Dimensionality Reduction. London, Springer Verlag.

Lemaître, C., Smach, F., Miteran, J., Gauthier, J.-P. and Atri, M. (2007). A comparative study of motion descriptors and Zernike moments in color object recognition. Proceeding of International Multi-Conference on Systems, Signal and Devices (SSD),Hammamet, Tunisia, IEEE.

Rellier, G., Descombes, X., Falzon, F. and Zerubia, J. (2004). "Texture Feature Analysis Using a Gauss-Markov Model in Hyperspectral Image Classification." IEEE Trans. on Geoscience and Remote Sensing 42(7): 1543-1551.

Smach, F., Lemaître, C., Gauthier, J.-P., Miteran, J. and Atri, M. (2007). "Generalized Fourier Descriptors with Applications to Objects Recognition in SVM Context." Journal of Mathematical Imaging and Vision 30: 43-71.

Tenenbaum, J. B., Vin de Silva and Langford, J. C. (2000). "A Global Geometric Framework for Nonlinear Dimensionality Reduction." Science 290: 2319-2323.

Vapnik, V. (1998). Statistical learning theory. New York, Wiley Interscience Publication.