Measuring vine leaf roughness by image processing

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ABSTRACT

The application of plant protection product has an important role in agricultural production processes. With current pesticides management, a huge amount of them are applied to worldwide orchards. In precision spraying, spray application efficiency depends on the pesticide application method, the phytosanitary product as well as the leaf surface properties. For environmental and economic reasons, the global trend is to reduce the pesticide application rate of the few approved active substances. Under these constraints, one of the challenges is to improve the efficiency of pesticide application. Different parameters can influence the pesticide application such as nozzle types, liquid viscosity and leaf surface. In this paper, we focus on the vine leaf surface properties determination and the discrimination between two kinds of vine leaves (Pinot and Chardonnay) for different stages of development by following their roughness growth. This discrimination allows studying the impact of the product behavior, and allows to adjust the product viscosity and spraying parameters according to the roughness and the stage of vine leaf development.
In this context, we propose to explore the performance of combination of Generalized Fourier Descriptor with Kernel Discriminant Analysis method using neural network. The results show that sufficient information can be obtained with this combination to characterize vine leaves.

Keywords: Texture, Analysis leaf surface roughness, Kernel Discriminant Analysis, Generalized Fourier Descriptor, Neural Network.

1. INTRODUCTION

The agrochemical dispersion may affect the environmental compartments such as: air, water, soil, due to surface runoff phenomena, leaching volatilization degradation and adsorption of pesticides in the soil. These processes involve health risks for workers, for all those that living near agricultural area and of course are causes to environmental contamination. The increasing attention of public institution to the promotion of the production processes at low environmental impact, it's progressively influencing the implementation of new devices to minimize the environment pesticides losses and risks for the operators. In order to improve targeting of the spray, it is important to know how formulation/liquid properties interact with the characteristics of the target plant to affect spray deposition. Surface properties and plant structure will change as the plant grows, and will affect the quantity of spray deposited and its distribution over the plant. For young plants, the size, the angle and the roughness of leaves are likely to become more pronounced as the plant old. In this framework, it is interesting to discriminate plant leaves by their stage of development and their surface proprieties.

In this work, we focus on the leaf surface texture, in particular the vine leaves by image processing. In this context, different researches have been proposed in the literature.

In (Backes *et al*, 2009) applied multi-scale fractal dimension to plant species identification by leaf textureHowever, experiments involve very limited data set which make them hard to evaluate. (Im *et al*, 1998.) used a hierarchical polygon approximation representation of leaf shape to recognize the Acer family variety, (Wang *et al*, 2002) gave a method which combines different features based on centroid-contour distance curve, and adopted fuzzy integral for leaf image retrieval. Moreover, (Oide and Ninomiya, 2000) select leaf shape images as neural networks input and applied a Hopfield model in a simple perceptron to Soybean leaf classification. In (Mokhtarian and Abbasi, 2004) used curvature scale space image to represent leaf shaped and applied it to leaf classification with self intersection. Moreover, (Fu and Chi, 2006) combined the thresholding method and back propagation neural network approach for vein pattern extraction from leaf images In the same area, other studies based on microscopic images of leaf surface are proposed. (Ramos and Fernandez, 2009) analyzed texture of leaf surface via the second order statistic using Co-occurrence matrix. (Journaux *et al*, 2011) proposed a classification between different species based on leaf surface texture using Generalized Fourier Descriptor and Support Vector Machine.

In the context of preliminary study, assessment study was done to estimate optical roughness of vine leaves based on different features extracted from power spectrum of microscopic images and co-occurrence matrices (Bediaf *et al*, 2013). The results showed that young leaves are rougher than matures leaves. Unfortunately, the features used to estimate leaf roughness are insufficient to discriminate between different kinds and ages of vine leaves. The main contribution of this work is to explore the performance of Generalized Fourier Descriptor (GFD) combined with kernel discriminate analysis method and neural networks to discriminate between two kinds of vine leaves (Pinot and Chardonnay) in different stages of development and follow their roughness growth.

2. MATRIELS AND METHODS

In the purpose of vine leaf discrimination, it is interesting to use texture analysis because of spatio-frequential aspect of the features that can be extracted. In order to test the proposed leaf classification, the experiments have been done on images acquired with a SEM microscope (Figure 1). These images represent various surfaces (above, below, with and without rib) of the vine leaves with different stage of development: "young" and "mature" leaves. When the principal rib measure between 5cm and 7 cm we consider a leaf as young. However, if the principal rib measures 12 cm or more the leaf is considered as mature leaf. Our data base is made up of 576 images. Each image has a scale of 100 µm and a resolution of 201x201 pixels adapting the scale to our biological application.

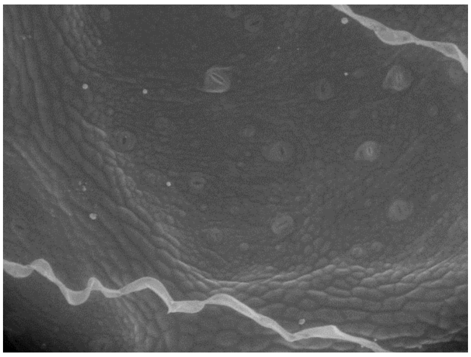
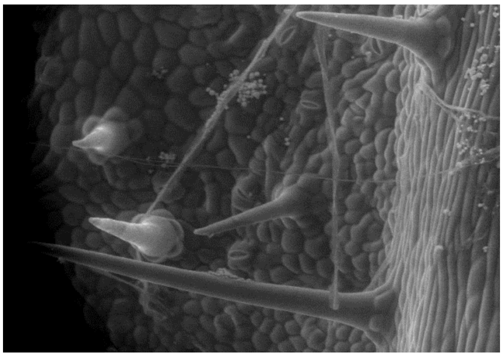

Figure 1.Leaf texture images for scale of 100 µm (Pinot and Chardonnay)

A natural texture classification is central problem in pattern recognition, it is known by its sensitivity to illumination, changes of scale and orientation. The overall performance of a texture classifier may be totally degraded if the unknown patterns to be classified are slightly rotated with respect to the training samples. In our case we consider the invariant features (scale, illumination and rotation) called Generalized Fourier Descriptor (GFD). (Smach *et al*, 2008) were proposed to extract a vector of robust texture features. However, this vector has high dimensionality which can cause erroneous classification due to the Hughes phenomenon (Hughes *et al*, 1968). To avoid this constraint, it is interesting to applied dimensionality reduction (RD) techniques in order to obtain representative data with reduced size. In this study, we propose to use nonlinear techniques as Kernel Discriminant Analysis (KDA) which is the most commonly used and the most suitable for our application.

2.1 Kernel Discriminate Analysis

KDA represents the extension of Linear discriminate analysis LDA. It is a nonlinear discriminating approach based on the kernel technique. It is developed for extracting the nonlinear discriminating features (scholkopf *et al, 1998*). Non linearity is introduced by mapping the data from the input space $\mathcal{R}$ to high dimensional features space F. The images of the pattern are linearly separable. Then by performing LDA in the feature spaces expressed by a kernel K, in terms of Mercer Kernel function (scholkopf *et al,1998*), (as polynomial, sigmoid and Gaussian kernel) we obtain a nonlinear representation in the original input space. In our studies, we have chosen the Gaussian kernel, which is fit with our objective (discrimination). The Gaussian kernel is defined as follows:

$$K(x,y) = e^{-\frac{||x-y||^2}{\sigma}} \qquad (1)$$

2.2 Generalized Fourier Descriptors

Feature extraction is the most important step in pattern recognition. Feature extraction needs to consider the effectiveness on both data representation and class separability. The classification of vine leaves texture is not obvious, because this type of texture (natural texture) is very sensitive to illumination, changes of scale and orientation. In this study we propose to use GFD which are very robust according to these constraints. The GFD have been defined by (Gauthier *et al*,1991) as follows:
Let f be as square sum able function on the plane, F its Fourier transform:

$$F(\xi) = \int f(x)e^{-i\langle x,\xi\rangle}\,dx \qquad (2)$$

If (λ, θ) are polar coordinates of the ξ, we denoted again by $F(\lambda, \theta)$ the Fourier transform of f at the point (λ, θ). (Gauthier et al) defined the mapping of:

$$D_f : \mathbb{R}_+ \rightarrow \mathbb{R}_+$$
$$D_f\,(\lambda) = \int_0^{2\pi} |F(\lambda, \theta)|^2 \; d\theta \quad (3)$$

Here D_f is the feature vector (Figure 2) which describes each texture image f and will be reduced by RD methods (see previously) and used as an input of our supervised classification method.

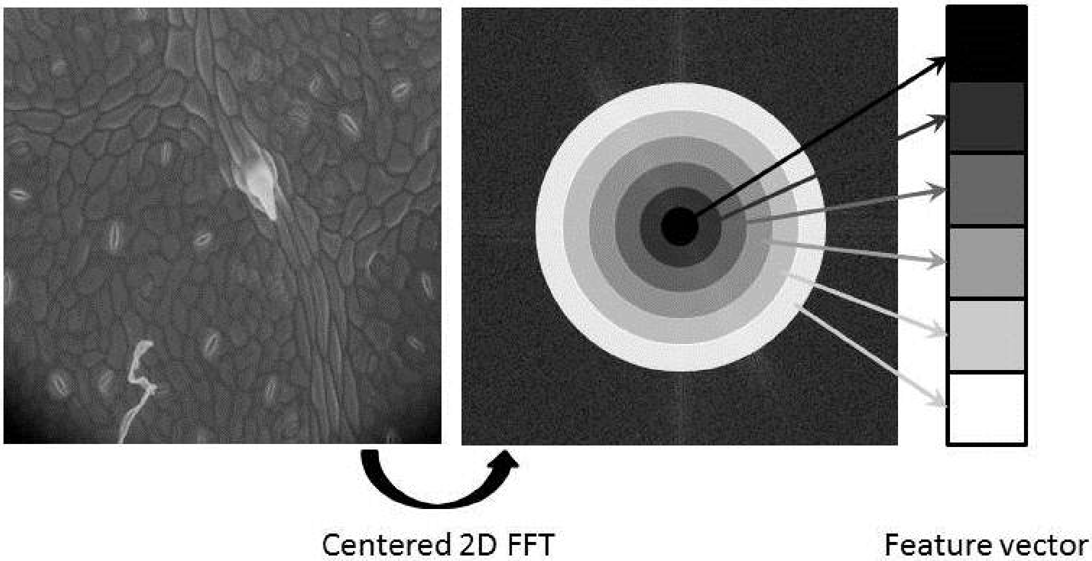

Figure 2. Procedure to find GFD texture vectors.

2.2.3 Multi-Layer Perceptron

In this study we use a neural network topology known as Multi-Layer Percetron (MLP). This type of classifier is known one hand by their robustness to strongly correlated parameters, the other hand, by his a resistance to the noise. The MLP is a feed forward networks with one input layers, one or more hidden layer and one output layer. Connections from higher to lower layers are not permitted. Each node in layer is connected to all nodes in the layer above it (khotanzad *et al*, *1990*). Training is equivalent to finding proper weights for all the connections such that desired output is generated for a corresponding input. The back-propagation algorithm is used to update weights of links between the input and the hidden layers. In our study, the result of dimensionality reduction of GFD vectors is the input of MLP. For the hidden and the output layer the tangent function is used as the activation function.

3. RESULTS

The proposed texture signature is applied on each vine leaf image selected. Each sample is characterized by GFD vector and the classes are known a priori. Therefore database is composed of four classes “young leaves of Chardonnay, mature leaves of Chardonnay, young leaves of Pinot and mature leaves of Pinot” and 576 x100 GDF vectors. All these information represent a high dimension and can cause erroneous classification. To avoid Hugh phenomena, it is important to reduce the size of the data. Then, we use kernel discriminant analysis to reduce dimensionality. To improve the accuracy of this experimentation, the database of vine leaves was divided into two data sets: one for training and one for testing. The combination of GFD and KDA appears to provide sufficient information to characterize vine leaf. In particular, this solution of texture classification enables us to separate our two types of agronomic images into four different clusters of old and young leaves of Pinot and Chardonnay as shown in Figure.3.

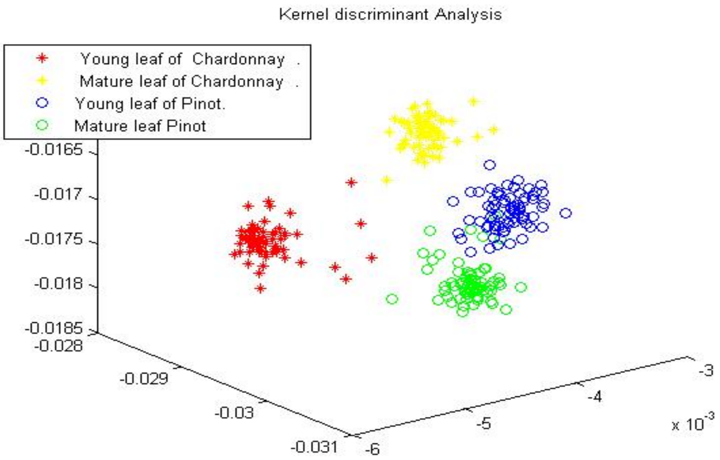

Figure 3 3D projection of the third component of KDA

The classification performance and the average error rate of classification are estimate by MLP. The mean square error (MSE) between the estimate class and the desired class outputs was used as the performance function during the training phase. The training phase is finished for a threshold MSE=0.001. The performance of the combination of GFD and KDA are given in table 1. The results are acceptable and the proposed method can be used as robust tool to follow the evaluation of growth and roughness of vine leaves.

Table 1. Classification rate of different kinds of vine leaves

Young leaf of Chardonnay	Mature leaf of Chardonnay	Young leaf of Pinot	Mature leaf of Pinot
100%	94.44%	97.22%	98.55%

4. CONCLUSION

In this paper, the discrimination between two kinds of vine leaves in different stages of development based on Generalized Fourier Descriptor is proposed. The combination of GFD and KDA appears to provide sufficient information to characterize vine leaves for different stages of development. This method could be used for other agronomic application such as discrimination between monocotyledon and dicotyledon vegetation or between hydrophilic and hydrophobic surface. This discrimination is very important for our project. It allows us to subsequently adjust the product viscosity and spraying parameters according to the variety and the stage of vine leaf development. Moreover, it allows us to define the impact of the behavior of the product for each grape vine, according to their textured surface properties of the leaf and its roughness. Indeed, it allows at the vineyard adjust viscosity of product used and spraying parameters (nozzle, velocity) depending on the kinds and stage of development of the leaf.

5. REFERENCES

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