ROUGHNESS EVALUATION OF VINE LEAF BY IMAGE PROCESSING

Houda Bediaf, Ludovic Journaux, Rachid Sabre, Frédéric Cointault
Agrosup Dijon, 26 Bd Docteur Petitjean,
BP 87999, 21079 Dijon Cedex, France
h.bediaf@agrosupdijon.fr

ABSTRACT
The study of leaf surface roughness is very important in the domain of precision spraying. It is one of the parameters that allow to reduce costs and losses of phytosanitary products and to improve the spray accuracy. Moreover, the leaf roughness is related to adhesion mechanisms of liquid on a surface. It can be used to define leaf nature surface (hydrophilic/hydrophobic). The main goal of this study is thus to estimate and to follow the evolution of leaf roughness using image processing and computer vision. The development and application of computer vision for measurement of surface leaf roughness using artificial neural networks will be described. The system for image acquisition of leaf surface consists of scanning electron microscope (SEM). The images of leaf surface are captured and analyzed to estimate the optical roughness. 2-D Fast Fourier Transform (FFT) algorithm and Co-occurrence Matrix are used for texture analysis. A multilayer perceptron (MLP) neural network is used to model and predict the optical roughness values.

KEY WORDS
Texture, Leaf roughness, Computer Vision, Neural Network

1 Introduction

Since the development of precision agriculture [1], much research has been done on the optimization of input in the field to reduce the environmental impact and to increase the yield, which is beneficial to farmers. In precision spraying research, one of the objectives is to minimize the volume of phytosanitary products applied in order to be more environmentally respectful with more effective plant treatments. Moreover, the main goal is to ensure that the sprayed products reach the plants targets, and to reducing losses occurred at the application time. Several studies have been done in this area, showing that leaf roughness is one of the most important parameter for adhesion mechanisms of liquids on a surface, and can be used to define leaf nature surface hydrophilic or hydrophobic [2].

Basically, a measure of surface roughness is done using stylus instruments, which require direct contact with the surface. Stylus instruments limited flexibility in handling the different geometrical parts to be measured. Moreover, this method is time consuming, cumbersome and therefore not suitable for high-speed and a large number of samples.

In order to overcome these problems, several investigations have been carried out using the non-contact optical methods for the assessment surface roughness[3, 4]. These methods are based on statistical measure of grey level images in the spatial domain [5]. In [6], Al-Kindi et al., propose to measure the surface roughness based on spacing between grey-level peaks and number of grey-level peaks per unit length of the scanned line in grey-level image. In [7] the authors used grey level histograms of images to characterize surface roughness and quality. They found that the ratio of the spread and the mean value of the distribution are nonlinear, increasing function of average surface roughness Ra (center line average). Moreover, other studies based on frequency domain for estimating surface roughness are proposed. In [8], the authors addressed the possibility of using the Fourier Transform (FT) to characterize the surface roughness in the frequency domain. However, in this approach only simple visual judgment of surface images in the frequency plane is considered. In [9], the estimation of surface roughness using a scanning electron microscope is reported. The result showed that the profile of surface could be obtained by processing back scattered electron signals. In [10], the authors used machine vision to estimate the surface roughness of machined parts generated by shaping and milling processes. The quantitative measures of surface roughness are extracted in the spatial frequency domain using the two dimensional Fourier Transform. In [11], the estimation of the surface roughness has been done using digital images of machined surfaces. The images are obtained by a machine vision system deliberately maintained at varying angles. The optical roughness surface values (Ga) estimated in all such cases are compared with the obtained values by using conventional stylus method (Ra). The results of this study showed that the optical roughness (Ga) and the roughness measured (Ra) are strongly correlated.

In precision agriculture, the leaf roughness is characterized by its hydrophobicity [12]. In this work, a new approach based on the hypothesis of the correlation between the optical roughness (Ga) and the roughness measurement (Ra) used for work pieces [13] is adapted to estimate vine leaf roughness. In this paper, the spectral and statistical texture parameters will be extracted and combined with an artificial neural network model to predict optical roughness.
of leaf. Based on this study, a statistical model can be built in order to adjust the viscosity of the phytosanitary product with the nozzle type according to the surface leaf roughness estimation[14].

2 Materials and Methods

2.1 Texture Parameters

In this work, our aim is to characterize a leaf surface with image processing and texture analysis using statistical and spectral parameters. These parameters will be combined with material parameters of spraying (nozzle, spraying speed) and viscosity of the phytosanitary product to study the behaviour of the spray on the leaf.

The roughness is one of the most important characteristic of leaf surface. In our study, in order to test the estimation of leaf roughness, the experiments include images (Figure 1) acquired with a SEM microscope. These images represent a various surfaces (above, below, with and without rib) of the vine leaves with different age "young" and "mature" leaves. For each class of vine leaf, 95 images have been acquired in order to get a representative statistical sample. Our dataset is made up of 570 images. Each image has a scale of 100 µm and a resolution of 201x201 pixels adapting the scale to our biological application.

In this work, surface roughness features are extracted based on spatial frequency domain using the 2-D Fast Fourier Transform (FFT) algorithm. Five frequency features proposed in [11] will be used to characterize the leaf surface roughness.

2.1.1 The Fast Fourier Transform (FFT) Analysis

Let \( f(x, y) \) be the grey level of a pixel at \((x, y)\) in the original image of size \( N \times N \) pixels centred on the origin. The discrete 2-D Fourier transform of \( f(x, y) \) is given by

\[
F(x, y) = \frac{1}{N^2} \sum_{x=-N/2}^{N/2-1} \sum_{y=-N/2}^{N/2-1} f(x, y) \exp(-j2\pi(xu + vy))
\]  

(1)

for \( u, v = -\frac{N}{2}, -\frac{N}{2} + 1, \ldots, 0, 1, \ldots, \frac{N}{2} - 1 \).

The Fourier transform is generally complex so \( F(u, v) \) can be written as:

\[
F(u, v) = R(u, v) + jI(u, v)
\]

(2)

where \( R(u, v) \) and \( I(u, v) \) are the real and imaginary parts of \( F(u, v) \), respectively.

The power spectrum \( P(u, v) \) of \( f(x, y) \) is defined by

\[
P(u, v) = |F(u, v)|^2 = R^2(u, v) + I^2(u, v)
\]

(3)

The normalized power spectrum, which has characteristics of probability distribution, is defined as

\[
p(u, v) = \frac{P(u, v)}{\sum_{(u,v)} P(u, v)}
\]

(4)

where \( P(u, v) \) is the power spectrum of the image \( I(x, y) \). As previously said, five frequency features are used, described in the next.

2.1.2 Major Peak Frequency \( F1 \)

The major peak frequency is defined as

\[
F1 = \sqrt{(u_1^2 + v_1^2)}
\]

(5)

where \((u_1, v_1)\) are frequency coordinates of the maximum peak of the power spectrum, i.e.

\[
p(u_1, v_2) = \max\{p(u, v), \forall (u, v) \neq (0, 0)\}
\]

(6)

The parameter \( F1 \) corresponds to the distance of the major peak \((u_1, v_1)\) from the origin \((0, 0)\), in the frequency plane.

2.1.3 Principal Component Magnitude Squared \( F2 \)

Principal component magnitude squared is defined as

\[
F2 = \lambda_1
\]

(7)

Where \( \lambda_1 \) is maximum eigenvalue of covariance matrix of \( p(u, v) \). The covariance matrix \( M \) is given by:

\[
M = \begin{bmatrix}
Var(u^2) & Var(uv) \\
Var(vu) & Var(v^2)
\end{bmatrix}
\]

(8)

for which:

\[
Var(u^2) = \sum_{(u,v)\neq(0,0)} u^2 \cdot p(u, v)
\]

(9)
\[ Var(v^2) = \sum_{(u,v) \neq (0,0)} v^2 \cdot p(u, v) \quad (10) \]

\[ Var(uv) = Var(vu) = \sum_{(u,v) \neq (0,0)} uv \cdot p(u, v) \quad (11) \]

The parameter F2 indicates the variance of components along the principal axis in the frequency plane.

### 2.1.4 Average Power Spectrum F3

The average power spectrum is defined as

\[ F3 = \sum_{(u,v) \neq (0,0)} P(0,0)/S \quad (12) \]

where \( S = N^2 - 1 \) for a surface of size \( N \times N \).

### 2.1.5 Central Power Spectrum Percentage F4

The central power spectrum percentage is defined as:

\[ F4 = \frac{P(0,0)}{\sum_u \sum_v P(u,v)} \quad (13) \]

This parameter represents the ratio of the normalized power spectrum at the origin.

### 2.1.6 Ratio of Major Axis to Minor Axis F5

The ratio of major axis to minor axis is defined as:

\[ F5 = \sqrt{\frac{\lambda_1}{\lambda_2}} \quad (14) \]

where \( \lambda_1 \) and \( \lambda_2 \) are respectively the maximum and minimum eigenvalues of covariance matrix of \( P(u,v) \).

### 2.2 Optical Roughness

The optical roughness value \( (Ga) \) is defined as the arithmetic average of grey level intensity values [11]. It was estimated by:

\[ Ga = \frac{1}{n} \sum_{i=1}^{n} |g_i| \quad (15) \]

where \( g_i \) is the difference between the grey level intensity of individual pixels in surface image and the mean grey value of all the pixels under consideration.

### 2.3 Co-occurrence Matrix

Grey level co-occurrence matrix (GLCM) [15], is one of the most known texture analysis methods. The characteristics of images are estimated from the second-order statistical features by considering the spatial relationship of pixels in the image. A GLCM element \( P(\theta,d)(i, j) \) is the joint probability of the grey level pairs \( i \) and \( j \) in a given direction \( \theta \) separated by distance of \( d \) units. In order to estimate the similarity between different grey level co-occurrence matrices, Haralick et al. [15] proposed 14 statistical features extracted from them. In literature [16], five features are determined for texture discrimination: Energy, Entropy, Homogeneity, Contrast and Correlation.

\[ \text{Energy} = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_d^2(i, j) \quad (16) \]

\[ \text{Entropy} = - \sum_i \sum_j P_d(i-j)^2 \log P_d(i, j) \quad (17) \]

\[ \text{Homogeneity} = \sum_{|i-j|} P_d(i-j)/(1 + |i-j|) \quad (18) \]

\[ \text{Contrast} = \sum_{i} \sum_{j} (i-j)^2 P_d(i, j) \quad (19) \]

\[ \text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i, j)}{\sigma_i \sigma_j} \quad (20) \]

where \( \mu_i, \mu_j, \sigma_i, \sigma_j \) represent respectively the mean and variance respectively of rows and columns.

### 2.4 Artificial Neural Network

After the frequency and statistic analysis, an artificial neural network (ANN) is used, namely, the multi layer perceptron MLP, which is the most popular and widely used in many application like approximation and classification [17]. The MLP consists of one input layer, one or more hidden layers and one output layer. Each layer has several neurons and each neuron \( i \) in a layer is connected to the neurons \( j \) in the adjacent layer with different weights \( W_{i,j} \). Signals flow into the input layer pass through the hidden layers and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer linearly weighted by the interconnected values between neurons. The neuron then produces its output signal by passing the summed signal through a tangent sigmoid function:

\[ S_j = f(\sum_i a_i W_{i,j}) \quad (21) \]
The training of the network is done by using training set of samples. Each sample input corresponds to one output desired. The signal is propagated from the input layer until the output layer. The output value is compared with target value corresponding to the sample for measuring the error. An algorithm of back propagation [18] is used to update the weights of links in between the input and the hidden layer $W_{i,j}$ for minimizing the error on the entire training set:

$$W_{i,j} = W_{j,i} + \alpha S_j \Delta_i$$  \hspace{1cm} (22)

where $\Delta_i = Err_i f(\sum a_i W_{i,j})$ and $Err_i$ is the error of output unit $i$.

In our study, we have seven neurons in input layer, three in hidden layer and one in output layer. The tan-sigmoid transfer function was used in the hidden and output layer.

### 3 Results

In this section, experimental results are presented to evaluate the validity of optical roughness parameters and the performance of neural network for roughness assessment based on their prediction. Statistical and spectral parameters are used to estimate the optical roughness for 570 images of 201x201 pixels for vine leaves (pinot and chardonnay). Five frequency features (F1, F2, F3, F4 and F5), and co-occurrence matrix parameters (entropy, energy) are used with MLP to estimate optical roughness. The following parameters, F2, F3 and entropy allow to detect the presence of the rib on the leaf; the values of F2, F3 and entropy increase and the value of energy decreases when a rib, mushroom or hair exist on the face of the leaves (see Figure 2). For the correlation and homogeneity, the sensitivity of their variation is not significant according to the type of the leaves.

As shown in Table 1, the mean values of F2 and F3 for young leaves “yl” (285 images) are high in comparison with mature leaves “ml” (285 images), which can be explained by the hairiness of young leaves (Figure3). However, the mean values of F2 and F3 for leaves of chardonnay are higher than for the leaves of pinot. This is explained by a huge density of hair in leaves of chardonnay.

The optical roughness estimation allows to deduce that the young leaves are rougher than mature leaves for the two varieties. Moreover, it can be deduced that value of Ga increases if the image corresponds to ribs, hairs or mushroom. So, it is interesting to note that the mean value of optical roughness Ga of Chardonnay is more important than the leaves of pinot. As shown in Figure 4, the variation of optical roughness Ga and average power spectrum F3 are proportional and the variables are strongly correlated (R2=0.93).

Furthermore, it is observed that the high values of the central power spectrum percentage F4 and the ratio of major axis to minor axis F5 correspond to the upper face of leaves. This can be explained by the homogeneity of texture patterns and the reliefs amplitude of the ribs and the hairiness in the upper face are less than the lower face of the leaves (chardonnay and pinot) (Table 2).
Figure 5. Comparison between predicted roughness and optical surface roughness

<table>
<thead>
<tr>
<th></th>
<th>F4</th>
<th>F5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chardonnay face lower &quot;yl&quot;</td>
<td>87.63</td>
<td>1.65e009</td>
</tr>
<tr>
<td>Chardonnay face upper &quot;yl&quot;</td>
<td>95.5</td>
<td>2.55e009</td>
</tr>
<tr>
<td>Chardonnay face lower &quot;ml&quot;</td>
<td>86.19</td>
<td>1.56e009</td>
</tr>
<tr>
<td>Chardonnay face upper &quot;ml&quot;</td>
<td>96.64</td>
<td>2.74e009</td>
</tr>
<tr>
<td>Pinot face lower &quot;yl&quot;</td>
<td>92.91</td>
<td>2.50e009</td>
</tr>
<tr>
<td>Pinot face upper &quot;yl&quot;</td>
<td>104.05</td>
<td>1.44e009</td>
</tr>
<tr>
<td>Pinot face lower &quot;ml&quot;</td>
<td>89.15</td>
<td>1.80e009</td>
</tr>
<tr>
<td>Pinot face upper &quot;ml&quot;</td>
<td>94.86</td>
<td>2.18e009</td>
</tr>
</tbody>
</table>

Table 2. Mean values of F4 and F5 of lower and upper face of leaves.

In this study, a Neural Network has been developed. The following steps are considered in designing the network: Generation of data, Pre-processing of data, Design of the neural network elements, Training and testing of the neural network. In the training step, the algorithm of back propagation is commonly used because of its fast convergence and its accuracy. The neural network is generated with different numbers of neurons in the hidden layer, and different activation functions (sigmoid, linear function and tan-sigmoid.). As consequence, we found that three neurons in a hidden layer and the tangent sigmoid function give satisfactory results. The mean square error (MSE) between the predicted and the desired outputs was used as the performance function during the training phase. The training is finished for a threshold MSE = 0.001 or when the number of iterations equals 4500. The predictive performance accuracy of the network is determined by difference between the desired optical roughness and the calculated value of roughness. The absolute error between the optical roughness and the predicted optical roughness for leaves was less than 0.09. Thus, indicating the high accuracy of the proposed vision system and the ANN model. The comparison between the predicted optical roughness and the desired leaf optical roughness is shown in Figure 5. The result shows that ANN model was able to model and predict the optical roughness of leaf with a high accuracy with a determination coefficient of 95.05%.

In addition, these parameters are not able to classify the different vine leaves (pinot and chardonnay). The Figure 6 shows 3D data projection using Principal Component Analysis method. It is clear that the clusters are overlapping so we cannot separate them. However, it is not necessary to separate the clusters since the most important is to find textural signing for each grape of vine.

Figure 6. 3D data projection using Principal Component Analysis for plant of Pinot and Chardonnay

4 Conclusion

In this paper, a computer vision system suitable for non-contact measurement of surface roughness of leaves using multilayer perceptron (MLP) is described. The results show the ability of computer vision and neural network model to estimate the leaf roughness without damaging the leaf. The Fast Fourier Transform algorithm (FFT) and the co-occurrence matrix are used to predict leaf roughness. The results obtained for leaf roughness estimation are encouraging. However, for optimal characterization of vine grape variety, it is interesting to test other methods of texture analysis as Gabor Filter or local binary pattern [19]. As future work, and basing on this results, it is interesting to make a comparison between the optical and the physical leaf roughness. In addition, it is expected to study the spraying step and try to correlate the texture parameters with parameters of spray (nozzle) and viscosity of product to study the behaviour of the spray on the leaf.

References


