Information Stored in Coronas of Fruits and Leaves

Aleksander Sadikov, Igor Kononenko

University of Ljubljana,
Faculty of Computer and Information Science, Tržaška 25, 1000 Ljubljana, Slovenia
e-mail: aleksander.sadikov@fri.uni-lj.si

Abstract

We recorded coronas of apple tree leaves and fruits in order to monitor and compare their state under different conditions. The results of our study show that coronas of leaves and fruits give useful information about the health status of plants and about the sort. At the same time we have to conclude that for time being we were not able to extract any useful information for differentiation between organically and conventionally grown plants and for assessing vitality of apple trees grown from various rootstocks.

Introduction

Recently developed technology, based on the Kirlian effect, for recording the human/plant bioelectromagnetic (BEM) field using the Gas Discharge Visualization (GDV) technique provides potentially useful information about the biophysical and/or psychical state of the object/person [1]. The recorded BEM fields, also called coronas, are then processed with specialized software developed by us and described by a set of numerical parameters. The subsequent analysis is based on these parameters.

Our motivation for measurement of BEM fields of leaves and fruits of plants with Kirlian photography stemmed from three observations:

(a) relatively successful use of Kirlian photography for medical diagnostic purposes, especially as an early warning system for detecting changes in the state of a human organism [1,2];
(b) previous research proved that it is possible to detect and find useful information in BEM fields of seeds of plants [4] as well as other non-human objects [3,5];
(c) a method of acquiring information on the state of a plant would be very useful.

The main goal of this ongoing study is to find out if and how vitality of plants subjected to various scenarios can be monitored with the use of Kirlian photography. Special emphasis is given to early detection of lowered plant vitality due to infection or improper conditions. The preliminary goal was to determine a good way of recording the BEM fields of leaves and fruits. This goal was successfully met and its implementation is partially described in [6].

Experiments and their goals

The experiments were conducted in cooperation with the Swiss based Research Institute of Organic Agriculture (FiBL) under the supervision of Dr. Franco Weibel, Head of Dept. Crop Production and Crop Quality. All decisions involving handling of plants were taken by a trained agronomist. In total we have up to now carried out 10 experiments involving different scenarios. These scenarios dealt with the problems presented in Table 1. Some technical details of the corona recordings can be found in [6].

There are four types of problems we have experimented with so far. These are problems dealing with different varieties, problems dealing with rootstocks, problems of the “sick vs. healthy” design and problems trying to separate between organically and conventionally grown plants. The goals of these problems were differentiation between varieties of apple trees, assessing vitality of various apple trees grown from various rootstocks, differentiation between infected and healthy trees and differentiation between organically and conventionally grown apples respectively.

Objects under observation were either leaves (Figure 1a), ripe apples (Figure 1b) or apple fruitlets (Figure 1c), and they were recorded at different GDV camera range settings. Number of recorded objects (learning cases) for a given problem varies from 30 to 80 according to the possibilities and priorities at the moment of recording. The problems are almost exclusively designed as two class problems and we tried our best to ensure that classes are as equipollently represented as possible.

Analysis and results of the experiments

As mentioned in the introduction the first step of the analysis process is transformation of obtained data into a more suitable form. For this we developed special software called GDV Assistant

problem	object	#ranges	#instances	#classes	majority class (%)
variety s41 vs s50	leaf	2	70	2	50
sick vs healthy tree	leaf	2	70	2	50
rootstocks: REM7, REJG, ARM7, ARJG	leaf	3	80	4	25
rootstocks: resi vs arriwa	leaf	3	80	2	50
rootstocks: M7 vs JG	leaf	3	80	2	50
conventional vs organic	ripe apple	4	59	2	51
rootstocks: M7 vs S2	apple fruitet	4	30	2	50
variety rajka vs rosana	apple fruitet	4	70	2	57
sick vs healthy fruitlets	apple fruitet	4	80	2	50
sick vs healthy leaves	leaf	3	40	2	50

Table 1 Basic characteristics of performed experiments

that is described in detail in [7]. As input it takes images of recorded coronas and returns a desired set of numerical parameters describing inputted coronas.

Numerical parameters we used were: Absolute area of the corona, Noise deleted from the image, Form coefficient, Form deviation, Average streamer width, Corona entropy, Fractal dimension, Average brightness, Brightness deviation, Brightness skewness, Brightness stability, Brightness entropy, Number of separated fragments in the image, Average area per fragment, Deviation of fragments' areas and 7 parameters based on geometric moments as defined by Hu [8]. In total we used 22 parameters, about half of them already well known in GDV community and half newly defined or taken from other fields by us. The new parameters are briefly discussed in the following paragraphs, while thorough description is given in [7].

Form deviation (FDev) is very similar to Form coefficient. It is also defined on the basis of curves of constant luminosity (isolines) that are defined in [10]. We created this parameter to emphasize the important changes in corona's form even more than Form coefficient already does. The formula is:

$$FDev = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(F[n] - avgF\right)^2}$$

where *F[n]* is the distance between center of corona and n-th point on the isoline and *avgF* is the average distance between the center of the corona and the isoline.

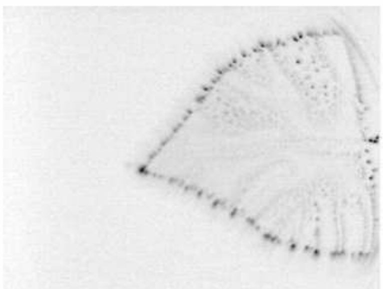

Figure 1a Leaf corona

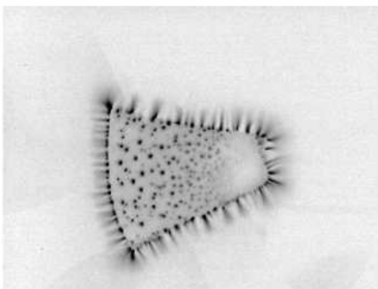

Figure 1b Ripe apple corona

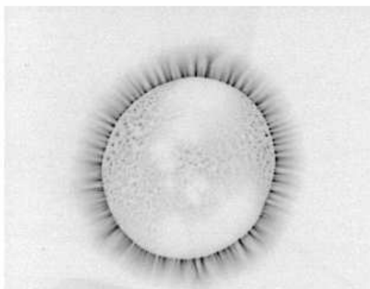

Figure 1c Apple fruitlet corona

To further extract the information contained in the corona's histogram we defined three additional parameters based on it. These are Brightness skewness (ν_3), Brightness stability (ν_4) and Brightness entropy (H) and they respectively give us information on the slope, stability and uniformity of frequency distribution of corona's brightness. Formulas are:

$$\mu_3 = \sum_{i=0}^{L-1}\left(i - m_1\right)^3 P_i, \quad \nu_3 = \frac{\mu_3}{\mu_2^{3/2}}$$

$$\mu_4 = \sum_{i=0}^{L-1} (i - m_1)^4 P_i, \quad \nu_4 = \frac{\mu_4}{\mu_2^2}$$

$$H = -\sum_{i=0}^{L-1} P_i \log P_i$$

where m_1 is average brightness of the corona, P_i is relative frequency of i-th brightness level and L is the number of brightness levels.

Hu's parameters are actually functions defined upon centralized geometric moments of the corona. Centralized geometric moments are defined with the formula:

$$\mu_{pq} = \sum_{x \in R} \sum_{y \in R} (x - \bar{x})^p (y - \bar{y})^q f(x, y)$$

where x and y are coordinates of a pixel of the corona and $f(x,y)$ is the pixel's brightness. Apart from their informational value the most coveted value of Hu's parameters for our experiments is that they are independent on the corona's size, rotation or translation in the image. This means that we can compare objects of different sizes (e.g. leaves) without worrying how the size (or rotation or translation) affects the results.

After obtaining numerical descriptions of the coronas we analyzed them with several machine learning tools. Our first choice was decision tree generating system See5 developed by Prof. Quinlan [9], because of its recognition in the AI community. Additionally we used the CORE system [11] developed by Dr. Marko Robnik-Šikonja to search for the possible dependencies between the given parameters that See5 is unable to detect and use. We used CORE in two ways – to generate a decision tree using ReliefF evaluation function and to generate a decision tree with the use of constructive induction (CI). We also used the Orange software package [12] developed by mag. Janez Demšar and doc. dr. Blaž Zupan to search for a hierarchy of parameters that best suits our problems with the technique called functional decomposition.

All the results were obtained using leave-one-out testing method and are presented in Table 2. The results represent classification accuracy (in %) averaged over all available ranges for each given problem. The last column represents classification accuracy of a random classifier based on majority class (guessing) for comparison purposes.

The highlighted rows mark problems where we achieved significantly better results than random classification. We can see that we were successful with problems dealing with differentiation of tree variety and problems dealing with differentiation of sick from healthy trees. For other two types of problems we were not able to extract much useful information from the recorded coronas.

problem	see5	core.relief	core.CI	f. decomp.	random cl.
variety s41 vs s50	**68**	**69**	**70**	**75**	**50**
sick vs healthy tree	**84**	**81**	**81**	**84**	**50**
rootstocks: REM7, REJG, ARM7, ARJG	25	29	30	0	25
rootstocks: resi vs arriwa	50	54	54	50	50
rootstocks: M7 vs JG	32	48	50	0	50
conventional vs organic	36	46	37	24	51
rootstocks: M7 vs S2	43	49	54	0	50
variety rajka vs rosana	**75**	**77**	**82**	**79**	**57**
sick vs healthy fruitlets	**72**	**74**	**68**	**76**	**50**
sick vs healthy leaves	48	50	56	0	50

Table 2 Results of performed experiments

Two comments are needed. First, the results presented are averaged over all available ranges and therefore are not the selection of the very best results achieved. These at least for time being give a more realistic picture, since we have not found any range that would be best for any given problem yet. Second, leaves under observation in scenario "sick vs healthy tree" could be quite clearly classified with the naked eye, while apple fruitlets in scenario "sick vs healthy fruitlets" could not. Because of that we consider the latter our best achievement so far.

Conclusions

As a result of our experiments at FiBL Institute, a reliable method for recording BEM fields of leaves and fruits with Kirlian camera was developed and tested in practice. Also, our experiments with sick and healthy apple trees supports our initial hypothesis that BEM fields of leaves and fruits contain useful information for assessing the state of a plant and show that there is sense in continuing this branch of our research. Machine learning techniques proved to be worthwhile in extracting this information.

For scenarios dealing with rootstocks the results showed that we could not obtain much information useful for this problems. In the scenario "organically vs. conventionally grown apples" only one experiment was carried out, so we consider the results inconclusive. At least one more experiment will be carried out in the future.

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References

[1] K. Korotkov, *Aura and Consciousness: A New Stage of Scientific Understanding*, St. Petersburg, Russia. State Editing & Publishing Unit "Kultura", 1998.

[2] T. Zrimec, I. Kononenko, Feasibility analysis of machine learning in medical diagnosis from aura images, *Proc. Int. Conf. KIRLIONICS-98 (Abstracts)*, St. Petersburg, June 1998, pp. 10-11, 1998.

[3] D. Skočaj, I. Kononenko, I. Tomažič, Z. Korošec-Koruza, Classification of grapevine cultivars using Kirlian camera and machine learning, *Research Reports, Biotechnical Faculty, University of Ljubljana, 75-1*, pp. 133-138, 2000.

[4] M. Čater, F. Batič, Determination of seed vitality by High Frequency Electrophotography, *Phyton, Annales Rei Botanicae (Horn, Austria), Vol. 38, Fasc. 2*, pp. 225-237, 1998.

[5] I. Kononenko, T. Zrimec, A. Sadikov, D. Skočaj, GDV images: Current research and results, *Proc. New Science of Consciousness*, Ljubljana, October 2000, pp. 65-68, 2000.

[6] A. Sadikov, *Recording Bioelectromagnetic Fields of Apple Leaves*, Technical report, Faculty of Computer and Information Science, Ljubljana, 2000.

[7] A. Sadikov, *Računalniška vizualizacija, parametrizacija in analiza slik električne izpraznitve plinov*, magistrsko delo, Faculty of Computer and Information Science, Ljubljana, 2002.

[8] M.K. Hu, Visual Pattern Recognition by Moment Invariants, *IEEE Tr. on Information Theory*, Vol. IT-8, pp. 179-187, 1962.

[9] J.R. Quinlan, *C4.5 Programs for Machine Learning*, Morgan Kaufmann, 1993.

[10] K.G. Korotkov, D.A. Korotkin, Concentration dependence of gas discharge around drops of inorganic electrolytes, *Journal of Applied Physics*, Vol. 89, pp. 4732-4736, 2001.

[11] M. Robnik-Šikonja, *Lastnosti in uporaba hevristične funkcije Relief v strojnem učenju*, doktorska disertacija, Fakulteta za računalništvo in informatiko, Ljubljana, 2001.

[12] J. Demšar, B. Zupan, *Orange: machine learning library in Python*, http://magix.fri.uni-lj.si, 2001.