

Analyzing Coronas of Fruits and Leaves

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Abstract

We implemented a system GDV Assistant for parameterization and visualization of coronas of humans and plants. Besides standard parameters, developed by the team of prof. Korotkov, our program includes some additional numerical parameters. In last few years in several studies we recorded coronas of apple tree leaves and fruits in order to verify and compare their vitality under different conditions. We used GDV Assistant for preprocessing and for numerical parameterization of coronas and we used various machine learning algorithms for analyzing the databases of parameterized corona pictures. The results of our studies show that coronas of leaves and fruits give useful information about the stress status of plants and about the variety. However, we were not able to differentiate between organically and conventionally grown fruit which were similar in their standard quality parameters such as fruit flesh firmness and sugar content.

1 Introduction

Recently developed technology, based on Kirlian effect, for recording the human/plant bioelectromagnetic field using the Gas Discharge Visualization (GDV) technique provides potentially useful information about the biophysical and/or psychological state of the object/person (Korotkov, 1998). The recorded coronas are then processed with GDV Analysis software and described by the set of numerical parameters. In the previous study (Skocaj et al., 2000) we recorded coronas of grape berries and have shown that standard numerical parameters of coronas can be used to successfully classify berries according to infection and sort.

In studies, described in this paper, we were interested in vitality of plants in various stress status (healthy versus infected plants), different varieties, different rootstocks and grown under different systems (organic versus conventional; various fertilization

methods). The recordings were done at the Institute for Organic Agriculture FiBL at Frick, Switzerland. In order to improve the parameterization of pictures of coronas we developed a system GDV Assistant (Sadikov, 2002) which implements several additional numerical parameters for describing coronas of human fingers and plants. We used several different machine learning algorithms for analyzing the parameterized coronas. For an introduction to machine learning paradigm see for example (Mitchell, 1997).

The paper is organized as follows. We start with description of new parameters, introduced by the GDV Assistant system. We follow by describing our recording methodology for obtaining coronas of plants. Section 4 describes various classification problems obtained by recording coronas of plants under various scenarios. Section 5 briefly describes machine learning algorithms used in our study and Section 6 provides results of the analysis. Finally, in Section 7 we conclude and give some ideas for further work.

2 GDV Assistant

GDV Assistant (Sadikov, 2002) was implemented in order to allow more flexible analysis of coronas than provided by standard GDV software suite (Korotkov, 1998). We used the first nine numerical parameters, as returned by GDV Analysis: A1. Area of GDV-gram, A2. Noise, deleted from the picture, A3. Form coefficient I, A4. Fractal dimension, A5. Brightness coefficient, A6. Brightness deviation, A7. Number of separated fragments in the image, A8. Average area per fragment, A9. Deviation of fragments' areas. We used also two parameters, defined by Korotkov and Korotkin (2001): *average streamer width* and *entropy of corona*. These parameters are a reimplementations of those in the original GDV software suite, therefore their exact values are usually somewhat different. Besides we defined four additional parameters:

1. *form deviation*;
2. *normalized skewness of brightness*;
3. *normalized stability of brightness*;
4. *entropy of brightness*.

We also implemented and used seven parameters developed by *Hu* (1962).

Form deviation (FDev) is similar to Form coefficient I. It is also defined on the basis of curves of constant luminosity (isolines) that are defined in (Korotkov and Korotkin, 2001). We created this parameter to emphasize the important changes in corona's form even more than Form coefficient already does. The formula is:

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

To further extract the information contained in the corona's histogram we defined three additional parameters based on it. These are Brightness skewness (v_3), Brightness stability (v_4) and Brightness entropy (H) and they respectively give us information on the slope, stability and uniformity of frequency distribution of corona's brightness. Respectively, the formulas are:

$$\mu_3 = \sum_{i=0}^{L-1} (i - m_1)^3 P_i, \quad v_3 = \frac{\mu_3}{\mu_2^{3/2}}$$

$$\mu_4 = \sum_{i=0}^{L-1} (i - m_1)^4 P_i, \quad v_4 = \frac{\mu_4}{\mu_2^2}$$

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

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

Hu's parameters are actually functions defined upon geometric moments of the corona. They were developed and used with success in the field of pattern recognition. Geometric moments of level $(p + q)$ are defined with the following formula, where R is a set of pixels belonging to the image and $f(x,y)$ is brightness of a pixel with coordinates (x,y) :

$$m_{pq} = \sum_{x \in R} \sum_{y \in R} x^p y^q f(x, y), \quad p, q = 0, 1, 2, \dots$$

Center of gravity of R lies in the point:

$$\bar{x} = \frac{m_{10}}{m_{00}}, \quad \bar{y} = \frac{m_{01}}{m_{00}}.$$

If we move the origin of image's coordinate system into the center of gravity we obtain invariance of geometric moments regarding the location of R within the image. Such geometric moments are called centralized geometric moments of level $(p + q)$.

To further guarantee invariance of geometric moments regarding the size of R we normalize them as shown in the formula below. This gives us normalized centralized geometric moments.

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^r}, \quad (p+q) = 2,3,\dots, \quad r = \frac{p+q}{2} + 1$$

Finally, Hu's parameters are defined with the formulas below. They are additionally invariant to the rotation of R . This invariance is actually the strongest point of Hu's parameters; with them we can compare objects of different sizes without worrying about normalizing the parameters.

$$\begin{aligned} \phi_1 &= \eta_{20} + \eta_{02} \\ \phi_2 &= (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2 \\ \phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\ \phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\ \phi_5 &= (\eta_{30} + 3\eta_{12}) \cdot (\eta_{30} + \eta_{12}) \cdot ((\eta_{30} + \eta_{12})^2 - 3 \cdot (\eta_{21} + \eta_{03})^2) + \\ &\quad + (3\eta_{21} + \eta_{03}) \cdot (\eta_{21} + \eta_{03}) \cdot (3 \cdot (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) \\ \phi_6 &= (\eta_{20} - \eta_{02}) \cdot ((\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) + 4\eta_{11}(\eta_{30} + \eta_{12}) \cdot (\eta_{21} + \eta_{03}) \\ \phi_7 &= (3\eta_{21} - \eta_{03}) \cdot (\eta_{30} + \eta_{12}) \cdot ((\eta_{30} + \eta_{12})^2 - 3 \cdot (\eta_{21} + \eta_{03})^2) + \\ &\quad + (3\eta_{12} + \eta_{30}) \cdot (\eta_{21} + \eta_{03}) \cdot (3 \cdot (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) \end{aligned}$$

GDV Assistant differs from its predecessor GDV Analysis in one more detail – image preprocessing. To remove the noise, apart from removing fragments smaller than a specified threshold and pixels with brightness level (intensity) lower than another specified threshold, it also uses smoothening of the image. For this purpose it uses a simple, yet efficient, median filter. Preprocessing is always composed of all three aforementioned steps and is always applied before any calculation of numerical parameters.

3 Recording methodology

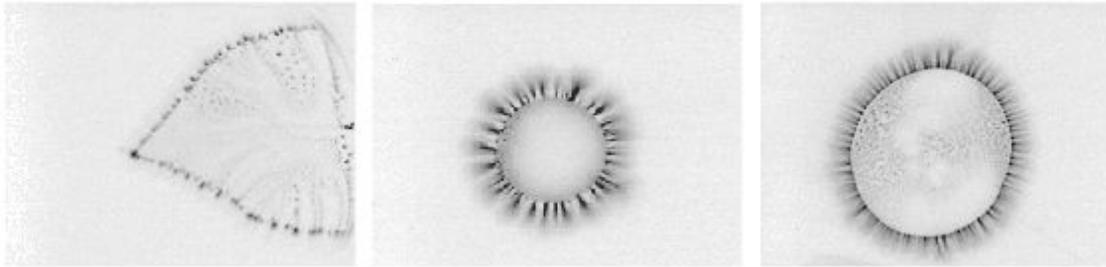


Figure 1 Coronas of a leaf (left), ripe apple (center) and apple fruitlet (right)

Before we could start conducting studies we had to find out how we could measure

leaves or fruits of plants with Crown-TV Kirlian camera. To this end we measured a large number of leaves and fruits from different plants (in the end we mainly focused on apple trees) with various settings for the camera parameters, various methods of positioning the object on the electrode and various methods of object grounding. We have developed separate recording methodologies depending on the object under observation. In the continuation we will separately describe these methodologies for different objects we recorded: leaves, ripe apples and apple fruitlets (at development stage "T", usually in first half of June).

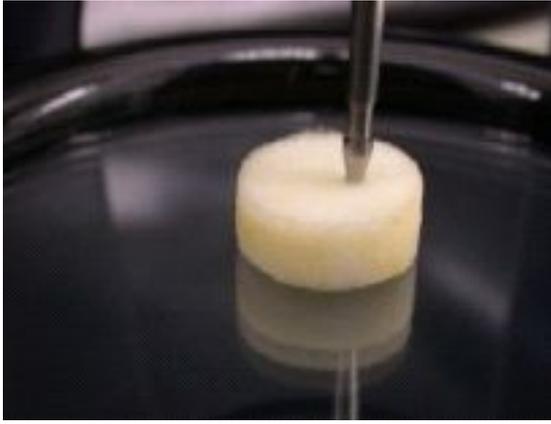
When measuring leaves the hardest problem to solve was their grounding and we spent a lot of time trying various methods before we eventually found a method that gives satisfactory results. Here is the detailed description of our method for recording leaves:

- the leaf is placed between two Petri dishes of slightly different sizes so that the smaller one can be put inside the larger one (with the leaf in between);
- the leaf is usually too large to fit on the electrode and the Petri dish in its entirety, therefore we record the upper part of it and the lower part with the stem is left sticking out of the Petri dishes;
- leaves are recorded face down;
- leaves are sometimes wet, they should be dried using a cloth;
- larger Petri dish is about the size of the camera electrode and is put on the electrode (see Figure 2);
- the grounding is best implemented by attaching a crocodile pin to the stem and the main vein of the leaf that is sticking outside of the Petri dishes, the pin is wired to the ground outlet of the camera;
- to firmly hold the leaf in its place weight of some sort needs to be put on top of the smaller Petri dish – we use a transparent glass filled with a certain amount of water to preserve access to outside light when making an ‘area shot’;
- some parameters describing the corona, i.e. area of GDV-gram, need to be normalized with the size of the leaf to account for the fact that leaves substantially differ in size;
- to calculate the area of the leaf (leaf size) we make a recording without covering the camera (to allow outside light), for this we need transparent weight mentioned above (Figure 2 is actually such an ‘area shot’) – area of the leaf is then easily obtained: we simply count the number of dark pixels in an area shot;
- camera parameters are Exposure = 1, Range = 2, 3 or 4 (preferably all are used with the same leaf, from smallest to largest to obtain different sets of data);
- sometimes several hours pass between picking and recording the leaves – meanwhile keep them in a plastic bag stored in a cooler box filled with 2-3 cooling elements and a moist sponge for humidity;
- leaves, that are most representative of the tree’s condition are those in the middle of the branch, grown in last year;
- electrode and both Petri dishes need to be cleaned often.



With ripe apples we had fewer problems than with leaves. Grounding proved not to be a problem. The main points of discussion were mostly which part of the apple to take and what shape it was supposed to be. Another decision to take was what to do with the skin of the apple. Agronomists felt that skin may be too easily influenced by external means beyond our control. This prompted us to record the apple tissue (the most consumer-relevant part of the apple) alone, cutting off the skin. Cutting is an intrusive method and we would like to avoid it, but the fact that ripe apples are just too big to be recorded as a whole (because of the electrode size) meant that we could not avoid cutting them anyway.





Our methodology for recording bio-electromagnetic fields of ripe apples with the Kirlian camera is as follows. First we wash the apple with water and dry it with a towel. Then we pinpoint the sun and shadow side of the apple. These two points are diametrically opposed to each other. Sun side is the side of the apple that was exposed to the sun the most when the apple was growing and is usually the most coloured part of the fruit. The point from where in the apple we extract the tissue is located exactly in the middle between the sun and shadow sides. This somewhat eliminates the effect of positioning the apple has while growing with respect to the sun (see last part of this chapter for discussion on this effect). At the point of extraction we cut off the skin and take out a cylindrical part of the apple tissue with a special excision tool (Figure 3). It is important to first cut off the skin, because this way we can extract the tissue with less pressure and risk of tissue damage while intruding the tool. From the cylinder of apple tissue extracted, a smaller cylinder of 5 mm height is gained by cutting the original core one centimeter under the former apple surface. This gives us a standard piece of apple tissue, which is cylindrically shaped with a diameter slightly more than one centimeter (Figure 4). The sample is then positioned on the electrode, grounded using GDV Materials Testing Kit and recorded (Figures 5 and 6).

Apart from standardizing the way of obtaining a recording sample another benefit of this method is that the sample's cylindrical shape guarantees a roughly circular corona. Circular coronas have the advantage that they are similar in shape to coronas of human

fingers for which there was the most scientific interest and hence the most methods of describing them with numerical parameters. This is also true for our own analytical program GDV Assistant, which we used for analysis during our experiments.

Our recording methodology for fruitlets is relatively simple. After picking, they are stored in a cooling box exactly the same way as the leaves. Before recording they are dried with a towel, they cut in half. Moistness from the cut is removed by a paper towel. The half with the stem is then put on the electrode face down and grounded much the same way as the ripe apples are (see Figures 5 and 6).

An extensive amount of measuring series was devoted to two important questions affecting the recording methodology:

- (a) What (if any) is the effect of the position the measured tissue had within the apple (sun-side or shadow-side; stem-side or calix-side)?
- (b) Is the information apple contains stored in its skin or its tissue?

To find out the answers to these questions we took four (for some even eight) samples from each observed apple: one from the sun side, one from the shadow side and two from in between both sides (neutral). Along with the recording of the tissue we also recorded the corona of the skin alone. Skin was approximately one millimeter thick.

The analysis, visual and numerical, showed that different tissue samples from the same apple did not differ significantly, while there were differences between tissue and skin samples. However, on the basis of these differences, we could not conclude whether skin or tissue carries more relevant information for our intended purposes.

Because there were no systematic differences of the kind or location of the tissue we decided to stick with our agronomically founded philosophy to sample between sun and shadow sides. Until there is any evidence that some other methodology can give better results this will be our default recording methodology for ripe apples.

4 Studies of apple fruits and leaves

4.1 First study

In the first study we recorded coronas of apple tree leaves and fruits in order to verify and compare their stress status or “vitality” under different conditions. The plants were provided by the Institute of Organic Agriculture FiBL in Frick, Switzerland and were recorded in years 2000 and 2001. Leaves and fruits were recorded in 10 different scenarios with different number of recordings. Each object was recorded several times using a different range for Crown-TV camera. Table 1 summarizes the available databases of GDV images of leaves and fruits for the first study.

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 (J-TE-G)	leaf	3	80	2	50
conventional vs organic	ripe apple	4	59	2	51
rootstocks: M7 vs S2 (Supporter 2)	apple fruitlet	4	30	2	50
variety: Rajka vs Rosana	apple fruitlet	4	70	2	57
aphid-stressed vs healthy tree	apple fruitlet	4	80	2	50
aphid-stressed vs healthy trees	leaf	3	40	2	50

Table 1 Different scenarios of the first study

4.2 Second study

The second study was also performed at FiBL Institute in Switzerland. It took place in October 2002. Two experiments dealt with differentiating organically grown apples from conventionally grown ones. The apples measured (variety Idared) in these two series originated from neighbored fruit farms (organic/conventional) and from a system comparison experiment (organic/conventional) at the Swiss Federal Research Station (RAC) at Fougères. Third experiment of this study was designed to investigate whether we can measure the effect of different fertilization methods by analyzing the corona images of apples grown in a long-term tree nutrition experiment. For this experiment we recorded 30 apples for each of five different fertilization methods, here denoted as v2, v3, v4, v5 and v10. This gave us a total of 150 samples.

In all measuring series with ripe apples and on each fruit we also assessed the most important standard quality parameters for fruit such as flesh firmness by a penetrometer, sugar content with a refractometer and acidity by titration, additionally we made a simple taste-test, giving points from 1 (very poor) to 5 (very good) by the same personnel who carried out the sample preparation and the GDV measurements.

Let us provide some details about the origin of the samples for this experiment. Apples were taken from the Kob trial (Weibel, 2001) performed by Franco Weibel and Andi Schmid at the Vogt organic farm in Remigen, AG, Switzerland. The apples are all of the same variety (Topaz), the only difference between them is the fertilization treatment they receive. Treatments taken under our observation were:

- v2: negative control, without compost, with PKCaMg addition;
- v3: fertilized with compost;
- v4: fertilized with compost of same raw material as v3, but made by a

- bio-dynamic recipe; no bio-dynamic preparations added during vegetation;
- v5: same as v4, except with bio-dynamic preparations added during vegetation 3 times per year on soil (bd 500) and on leaves (bd 501);
- v10: positive control, without compost, soil and leaf fertilizers applied, closest variant to conventional fertilization.

Specific information about the experiments from the second study is given in Table 2.

Problem	object	#ranges	#instances	#classes	majority class
conventional vs organic	ripe apple	4	80	2	50
conventional vs organic	ripe apple	4	60	2	50
fertilization method	ripe apple	4	150	5	20

Table 2 Experiments of the second study

4.3 Experimental design

All the experiments in both studies were performed in a similar fashion. We first recorded the images of selected leaves or fruits with the Crown-TV camera using the previously discussed recording methodology. For the purposes of analysis and differentiation we have described the obtained images with numerical parameters with the use of GDV Assistant program. Each sample was described with a set of numerical parameters described in chapter 2. Differentiation was then attempted with See5 software and potentially with other machine learning programs. Potential statistical analysis of the data was done with Microsoft Excel.

Unless specified otherwise the results were obtained using default settings of See5. Other settings were tried but did not give much improvement, if any. Testing method used was leave-one-out testing where number of samples was less than 100, otherwise 10-fold cross validation was used (for description of machine learning programs and testing methods see next chapter).

5 Machine learning

We used various machine learning algorithms in order to interpret the coronas, described with numerical parameters. Each example (in our case one example is one picture of corona) is described with a set of numerical parameters and is labeled with a class. The number of different possible classes for a given scenario indicates how difficult a priori is the particular classification problem. The actual difficulty depends on how informative various parameters are for the particular class. The number of training examples (coronas of plants) should be as high as possible. In our studies the number of training instances was limited with the number of specimens provided by FiBL and our recording capabilities.

We used See5 (Quinlan, 1993), which builds decision trees from a training set of

examples. Decision trees are then used to classify yet unseen examples into classes. The better the decision tree the more accurate this classification is. Quality of a decision tree is tested with a procedure called cross validation. It divides the training set into n subsets, constructs a decision tree using $n - 1$ subsets and then uses the generated tree to classify the examples in the subset that was left out. This classification is then compared to real classes for these examples. Accuracy of the decision tree is the percentage of correct classifications. This procedure is repeated n times, each time leaving out a different subset. Accuracy of the classification is finally calculated as the average of accuracies of n generated decision trees. 10-fold cross validation is cross validation with n set to 10. Leave-one-out is a special case of cross validation where n equals the number of examples in the training set. In this case each subset consists of only one example. We say that data contains useful information when a classifier's accuracy is significantly better than default classifier which simply classifies all the examples into the majority class.

Apart from See5 we have used an alternative program for building decision trees, CORE (Robnik-Sikonja, 1997). This program was instructed to use a different function – ReliefF (Kononenko, 1994) – while generating its decision trees, specifically targeted at detecting dependencies between parameters. Furthermore we have used CORE to automatically combine the initial numerical parameters using arithmetic (addition, subtraction and multiplication) and boolean (AND, OR) operators. This is known as constructive induction.

Yet another program we used is HINT (Zupan et al., 1999). We used its Orange machine learning suite implementation (Demsar and Zupan, 2003). The task of this program was to hierarchically group our initial numerical parameters. This sometimes improves classification accuracy and can also make explanations clearer. It works by the means of functional decomposition and is also a method of constructive induction.

6 Analysis of results

6.1 First study

In four classification problems (scenarios) we have got significantly better results than random classification. For other six problems we probably have to conclude that Crown-TV is not suitable for them. Results for all scenarios and all four machine learning methods are presented in Table 3. Last column shows how good a default classifier would be. Positive scenarios are highlighted. It can be seen that none of various machine learning methods holds any significant edge over the others. In the second study we therefore used only See5.

problem	see5	core.reliefF	core.CI	HINT	default 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 (J-TE-G)	32	48	50	0	50
conventional vs organic	36	46	37	24	51
rootstocks: M7 vs S2 (Supporter 2)	43	49	54	0	50
variety Rajka vs Rosana	75	77	82	79	57
aphid-stressed vs healthy trees (fruitlets)	72	74	68	76	50
aphid-stressed vs healthy trees (leaves)	48	50	56	0	50

Table 3 Classification accuracy of different machine learning methods

Table 4 gives results for four positive problems, where Crown-TV data provides useful information. We compare the classification accuracy of See5 (using leave-one-out testing and average over all available ranges of Crown-TV) on different subsets of parameters: all 22, without 7 Hu's parameters (=15), only 7 Hu's parameters, original 9 parameters plus 2 defined by Korotkov and Korotkin (2001), and only 11 new parameters.

Problem	All 22	All-Hu =15	Hu=7	GDV=9+2	New = 11
variety s41 vs s50	68.4	72.0	75.5	72.0	67.7
sick vs healthy tree	83.6	82.2	84.3	80.0	84.3
variety Rajka vs Rosana	75.4	70.0	69.3	74.3	72.5
aphid-stressed vs healthy tree (fruitlets)	71.9	73.1	59.0	67.8	74.0

Table 4 Classification accuracy with different subsets of parameters

The results indicate that no subset of parameters outperforms all the others in all cases. It seems that Hu's parameters are quite robust and together with our 4 additional parameters (altogether 11 new parameters – last column of Table 4) the robustness even increases, although the results are not stable.

6.2 Second study

Both experiments dealing with differentiating organically grown apples from conventionally grown ones turned out negative. Counting a similar experiment from the first study, this means that all three experiments dealing with this type of differentiation were negative. It has to be noted, that in these cases standard quality parameters didn't differentiate the samples either. On the basis of these series we probably have to conclude that Crown-TV is unable to provide us with complementary or organic-specific information in addition to what can be assessed by standard quality

parameters.

Classification attempts with See5 for the fertilization experiment were also negative. However, here we would be satisfied with a less powerful result of differentiating between groups and not necessarily classifying each sample into its class. The question then was whether there is a difference in any of the GDV parameters between one fertilization method from the other. To find this out we performed statistical t-tests for all GDV parameters on all pairs of fertilization methods. Results were positive for parameters area, noise and brightness deviation and are shown in Table 5.

TTesting	pair	area	noise	br.dev
	v2 vs v3	0.0000	0.0000	0.0009
	v2 vs v4	0.0074	0.0000	0.6455
	v2 vs v5	0.0531	0.0013	0.1898
	v2 vs v10	0.0675	0.1216	0.4040
	v3 vs v4	0.0105	0.0349	0.0056
	v3 vs v5	0.0002	0.0000	0.0207
	v3 vs v10	0.0009	0.0000	0.0001
	v4 vs v5	0.2293	0.0002	0.4442
	v4 vs v10	0.3435	0.0000	0.2150
	v5 vs v10	0.9077	0.0442	0.0338

Table 5 Results of t-tests for positive GDV parameters

Numbers in Table 5 represent probabilities that the two groups of samples come from the same population according to the observed GDV parameter. For example, value 0.0531 in the fourth row of the third column means that there is 5.31% probability that groups v2 and v5 come from the same population. With bold font we marked those probabilities that are less than 5% (a statistical standard). For these cases we can claim that observed GDV parameter(s) point out the differences between the groups and therefore show differences between fertilization methods. In Table 5 we included only GDV parameters that showed such differences.

7 Conclusions

GDV technology can provide useful information for distinguishing healthy and stressed plants and, in some cases, it can provide useful information for distinguishing different varieties of the same family of plants. It can also provide information for distinguishing fruits grown using different fertilization treatments. However, in our cases with fruit of very similar standard quality, we were not able to find complementary information to distinguish organically from conventionally grown plants.

Our four new parameters together with seven Hu's parameters seem to be valuable for

describing GDV images and can in certain cases provide better information than standard GDV parameters. It is especially useful that Hu's parameters do not need to be normalized with the size of the recorded object because they are insensitive to the layout, rotation and size of the object.

Our experience is that there is more information (or it is more easily extracted) in fruits than in leaves of plants. Fruits are also more easily handled during the recording phase of the experiments, especially so when working with standardized fruit cores. As a main result of the measuring series presented in this article we could investigate and establish an optimized sampling and assessment method for routine fruit quality measurements. Thus, for the future we can and plan to concentrate more on the measuring series themselves. The main goal remains: finding out a complementary and very sensitive method on not destroyed food tissue to differentiate vitality-related quality parameters more accurate than with standard analytical and mostly tissue-destroying methods.

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