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TOWARD NUMERICAL PRACTICES IN VARIETY TESTING: A RATIONALE TO SELECT THE MOST PROMISING TRAITS

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ABSTRACT

1. In this opinion paper, we focus on variety testing offices in the European Union. Variety testing nowadays is mainly done with traditional visual inspections. As a consequence, introducing automation and sensors in variety testing could lead to an increase of throughput together with a higher reproducibility. However the task is huge since there are thousands of characteristics to be measured within variety testing. We propose a rationale to select the characteristics which may be the most promising to benefit from an automation via numerical practices. An important criterion for variety testing is that the measurement have to be achieved with low-cost sensors. For illustration, we describe a strategy to select the most promising characteristics that we believe could benefit from such an integration with low-cost sensors for a small set of crops of major interest in food production.

INTRODUCTION

2. To commercialize a new variety of an agricultural or vegetable species in the European Union, a plant breeder has to follow a process managed by a national authority and delegated to an examination office (EO) that will describe and evaluate the variety for its registration on the national list. The national lists of all the EU Member States (MS) are compiled by the European Commission to form the Common Catalog allowing the variety to be marketed throughout the EU. Evaluation results including variety descriptions may also serve for the granting of Plant Variety Rights (PVR) both at the national and European Union level, as well as for certain crops- for the certification of seed lots. Depending on the MS, the legal mandate of a national examination office (EO) covers part or all of these missions. According to this framework, the EOs run field tests either under the supervision of their national competent authorities or upon request of the Community Plant Variety Office (CPVO) cpv (2020) in charge of granting PVR on the territory of the EU.

3. Currently a large majority of these tests are based on manual measurements performed from visual inspection. This method has consequences in terms of efficiency due to the time consuming nature of these tests. It is also an issue for the reproducibility of these tests when some characteristics are based on qualitative characteristics which may suffer from subjectivity in their assessment. Improving efficiency and reproducibility of these observations would be extremely useful for EOs that are continuously seeking for optimized testing methods implemented in testing protocols. It could also provide means to assess new characteristics developed in response to new agricultural constraints, particularly in the perspective of climate change. In addition, more efficient measurement methods would assist in addressing the challenge of the constant increase in the number of varieties that have to be tested. More reproducible measurements would also contribute to harmonizing practices between European Union EOs (supporting for example the use of historical data to predict the expected behavior of varieties toward different climatic scenarios). The described challenges encourage to head toward the use of sensors and numerical practices to progressively replace classical manual methods of examination whenever there is a need to speed up measurement or increase their reproducibility and objectiveness. The trend of using more and more imaging for plant science has started some decades ago and has been extensively reviewed (see Li *et al.* (2014); Qiu *et al.* (2018) for most recent ones) including with cost-effective strategies Reynolds *et al.* (2019b). While imaging modalities used in plant science and variety testing may be similar, the types of measures in plant science and variety testing differ either by their nature and technical aspects. So far few attention from the academic imaging community has

focus on these specific aspects of variety testing. This is what we propose in this short opinion article. Variety testing is performed among networks of offices and has to be accessible to breeders. As a consequence, measurements should rely on cost-effective technologies easy to be replicated. The article is organized as follows. After explaining the variety testing specificities, we propose a rationale for the selection of characteristics which may benefit the most from the use of low-cost imaging systems. This rationale is illustrated on some crops of major interest in food industry (wheat, maize, sunflowers and tomato). We then propose possible technologies for the measurement of these characteristics. We conclude by pointing toward the needs, challenges and opportunities for the deployment of low-cost imaging system in variety testing protocols.

VARIETY TESTING SPECIFICITIES

4. Two types of evaluation are mainly performed for variety testing. DUS (2020) tests (for Distinctness, Uniformity, Stability) are conducted to ensure that a new variety is distinct from existing varieties, that it is sufficiently uniform in its characteristics, and that the variety is stable with consistent phenotypic characteristics from one generation to the next. For most species, these tests are harmonized world-wide by UPOV members and are carried out according to standardized technical protocols (CPVO TPs), based on UPOV Test Guidelines and using reference plant material provided by the breeders. For example, for agricultural crops, morphological features and color are mostly used, as well as phenological features such as flowering and ripening phases. Some species are also tested for disease resistance. This produces a “variety description” (VD) which forms the identity card of the tested variety. The VDs are also used -as one tool amongst other- for the enforcement of the PVR to which they are associated. Thanks to the harmonization of the guidelines the members of the UPOV (2020) Convention may (if they wish to) accept DUS reports established by another UPOV member (meaning that a given DUS report established in one UPOV member can be used by another UPOV member as a basis for a decision to grant a PVR, without the breeder having to pay again for the same field tests but only an administrative fee of Swiss Fr 350). In terms of data processing DUS measurements correspond to a classification problem. Taking decision to classify is by nature a non-linear problem. As a consequence, it can be done with non-linear sensors and may not need fully linear and calibrated sensors. What needs to be calibrated is the performance of the classification, but this classification can be done on possibly distorted data provided distortion does not degrade classification performance. This means that DUS can, by nature, benefit from low-cost imaging systems.

5. The second type of evaluation is VCU (2020) tests (for Value for Cultivation, Use which are performed for all agricultural crops. The goal of these tests is to evaluate the variety’s suitability for growing in local agro-climatic conditions and the technical value of the harvest (e.g. protein, oil content,...). To qualify for registration, the new variety must have an “added value” in the country where it is evaluated. This is established by comparing it to a set of existing reference varieties, over two testing cycles consisting of 5 to 20 trials per year. Unlike DUS, VCU measurements are not harmonized among the countries. Also, in terms of data processing VCU, corresponds to a regression. It is therefore more demanding in terms of precision and less likely to benefit from low-cost imaging systems and will therefore not be addressed in this article. This choice here does not mean that VCU would be less important than DUS, but rather that DUS is more straight forward to address with low-cost systems (the point of view followed in this article) than VCU. Also, VCU characteristics have received relatively more attention than DUS from the imaging community for their applications in yield assessments, or their value as input data in crop models. For all these reasons we focus more on DUS characteristics in this article.

A RATIONALE TO IDENTIFY MOST PROMISING CHARACTERISTICS IN DUS PROTOCOLS

6. Assessment of DUS characteristic for each crop is explained in the UPOV Test Guidelines. This constitutes thousands of traits. Switching current manual practices to numerical practices will obviously require a lot of time and effort. In this section we propose a rationale to select the most promising characteristics to start the work. We first give the different types of measurement which are performed in DUS.

7. For the registration of new varieties, two modes of observations are currently performed. The first are visual observations (V) which rely on the expert’s judgment. It includes observations where the expert uses reference points (e.g. diagrams, example varieties, side-by-side comparison) or non-linear charts (e.g. color charts). Visual observations can also include sensory observations of the experts (smell, taste and touch). The second type is measurement (M), which correspond to objective observations relative to calibrated linear scales e.g. using a ruler, colorimeter, dates, counts, etc. These two types of observations can be recorded as a single record for a group of plants or parts of plants (G), or may be recorded as records for a number of single, individual plants or parts of plants (S). Therefore 4 possible combinations are found in DUS protocols:

VG: Visual assessment by a single record per group of plants or plant parts for the assessment of distinctness; VS: Visual assessment by individual records for each plant or plant parts; MS: Assessment by measurements and individual records for each plant or plant parts; MG: Assessment by measurement and one record per group of plants or plant parts.

8. Based on the four different types of assessment in DUS, we can consider that quantitative characteristics are the ones that suffer less from subjectivity in a classical human visual inspection. They are therefore suitable for a translation in automated, sensor-based protocols which can be compared with standard protocols. The most difficult objective characteristics to measure among these are specially those which are attached to the assessment of dynamical processes (emergence, time of flowering, ...). Difficulty comes from the fact that evaluation can currently be carried out only for a fixed and limited number of time points. Having continuous recording would possibly improve the accuracy of such monitoring. Second, one can focus on characteristics which are common to different crops so that the development of a sensor can actually serve several usages. Third, characteristics which are laborious to access in proxy detection, such as plant height, or ear size (especially in the field and for large crops at mature stage such as maize), could be assessed much faster with remote sensing technologies, such as Unmanned aerial vehicles (UAVs) and high-resolution cameras. At last, the quantification of characteristics, which could be measured at the same time with single snapshot acquisition such as diameter, length, number of grains and shape, would also be accelerated with the use of imaging systems.

9. Following the rationale described above, a list of characteristics to be chosen in priority can be extracted from the UPOV Test Guidelines. For illustration in this article, we applied this rationale to four crops of major importance for food industry and came up with the short list of Table 1.

CHALLENGES FOR LOW-COST IMAGING SYSTEMS DEDICATED TO MOST PROMISING CHARACTERISTICS

10. Imaging devices are nowadays largely available at low-cost, and are embedded in connected objects such as smart phones, tablets, or mini-computers which have been largely reviewed in the recent literature (Paulus *et al.*, 2014; Tsaftaris and Noutsos, 2009; Chéné *et al.*, 2012; Furbank and Tester, 2011; Pereyra-Irujo *et al.*, 2012; Reynolds *et al.*, 2019b; Roitsch *et al.*, 2019; Reynolds *et al.*, 2019a; Costa *et al.*, 2019; Bauer *et al.*, 2019; Coupel-Ledru *et al.*, 2019). These imaging systems and connected objects can be fixed on various devices such as Unmanned aerial vehicles (UAV), unmanned ground vehicles or connected sticks. To translate the current variety testing protocols into sensor-driven protocols, it would be more strategical to provide ergonomic systems directed carried by the variety testers. Handy cameras may be used in this context, but a more ergonomic alternatives may be wearable glasses positioned on the head of the testers and leaving both hands free for manipulation of the plants.

11. Some low-cost sensors are already available for the most-promising characteristics to be measured in the field as identified in the previous section. For repeated event measurements (e.g. monitoring of dynamic traits) time-lapse (TL) camera systems may be of help as they are capable to acquire images over larger periods without any user interaction. Such cameras are available of-the-shelf like Wild-Vision cameras wil (2020), originally designed as camera traps for animal photography, but also capable to deliver TL image series, and TL cameras for project, construction site or nature monitoring bri (2020). Modern DSLR cameras are equipped with internal TL mode or may be triggered with commercial external intervalometers and, finally, mini-computers like Raspberry Pi or micro-controllers like Arduino may also be used as intervalometers. For length annotation and measurements there exists a bunch of applications for smartphones. The application scenarios range from annotation like ImageMeter Pro lma (2020) to measurements of length and areas like in Smart Measure Sma (2020a), Smart Measure Tool Kit Sma (2020b), partly using augmented reality (AR) methods for measurement and display, e.g. Measure Tools AR ruler Mea (2020) and EasyMeasure Eas (2020).

12. The limitation of all these available technologies for variety testing is primarily due to image processing. Although a wide range of image processing softwares has been developed and archived, for an overview see (Lobet *et al.*, 2013; Lobet and Guillaume, 2017), only a very small selection of these softwares is exactly following the protocols of variety testing (Brewer *et al.*, 2006; Polder *et al.*, 2012). Moreover, the available softwares particularly dedicated to variety testing (Brewer *et al.*, 2006; Polder *et al.*, 2012) only focuses on post-harvest assessments in controlled environments. Also, unfortunately, available solutions are currently not accessible within applications specifically dedicated to manual rating in the field for variety testing such as Fie (2020). A simple and useful development would thus be to use the existing literature of algorithms, which is suited for variety testing, and implement it in Internet of Things (IoT) platform Ayaz *et al.* (2019) to record measurements and meta-data associated with variety testing.

13. Most of the recent literature in image processing now relies on Artificial Intelligence (AI) approaches like Convolutional Neural Networks (CNNs) deep learning Goodfellow *et al.* (2016). In this machine learning technique both features and decision making are learned simultaneously. This approach, which has been successfully applied in all domains including plant imaging Mohanty *et al.* (2016); Kamilaris and Prenafeta-Boldú (2018); Singh *et al.* (2018), has produced state-of-the-art performances for all image processing tasks. Standard deep neural networks are now accessible to address many types of problems, like for image classification Krizhevsky *et al.* (2012); landola *et al.* (2014), for object recognition Redmon and Farhadi (2018); Ren *et al.* (2015), for segmentation Ronneberger *et al.* (2015); Badrinarayanan *et al.* (2017). However, most of these architectures are very demanding in terms of computation not only during the training but also during real-time applications. For these reasons specific light version have been designed to run in embedded mode. For variety testing it would be particularly important to consider such light architectures for field applications with smart phones as recently stressed in Atanbori *et al.* (2020).

CONCLUSION AND PERSPECTIVES

14. In this opinion paper, we have highlighted the need for the development of low-cost imaging and image processing algorithms to serve in the acceleration and the increased objectivity of characteristics assessed in variety testing. Given the huge amount of characteristics to be measured in variety testing we have proposed a rationale for the selection of the ones that are the most likely to benefit from cost-effective technologies. While all technologies are available in terms of sensors and algorithm, the remaining challenge consists in assembling these technologies with ergonomic vectors and softwares.

15. It would also be interesting to tackle the question of other characteristics assessed visually such as color of fruit, shape of plants or detection of the presence of disease. Such visual characteristics could benefit from low-cost sensor with colorimeter or novel and affordable 3D LIDARS. A calibration step would be necessary to adapt the scales of the expert with the measure from these sensors. Also, other crops could be included within this exploratory research. Finally, it should also be discussed how these methods could be described and implemented in the relevant technical protocols, potentially UPOV Test Guidelines and CPVO TP. One has to keep in mind that the current observation time for one DUS characteristic by an expert is very often shorter than the image acquisition and processing of this characteristic. The efficiency of the human variety examiner should be improved when several DUS characteristics can be assessed from one image of pot, plant, organ.

16. Another perspective would be to analyze the need for sensors in VCU testing as well. As mentioned earlier, the current situation is that VCU testing protocol for species is not normalized between European Union countries, due to the specific conditions and needs (climate, soil, diseases...) of each country, which drives local evaluation that differs from one country to another. One way to support VCU assessment would be to select phenotypic characteristics which can constitute input for agronomical models (White *et al.*, 2013). Such models have been designed for phenotyping purposes with some high resolution sensors. In this perspective, it would be interesting to analyse what the effect of lowering the resolution would be while keep the predictive value of the agronomical models of the literature. Another way is the use of sensors and data fusion to identify DUS and VCU characteristics. Those perspectives open up analytical approaches to be investigated. Last, VCU characteristics assessment such as biotic and abiotic stresses on plants, quality of fruits need also other types of more expensive imaging systems (fluorescence, multispectral and hyperspectral near infrared, thermal, LIDAR) (Li, 2014; Chunjiang, 2019). Lowering the cost of these imaging systems could, therefore, significantly increase the potential impact of sensor-based DUS and VCU characteristics assessment and help the seed sector in general.

CONFLICT OF INTEREST STATEMENT

17. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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