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The Examples of Machine Vision in Agriculture

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Abstract— **Machine vision has been involved in the research and practical application of various phases of agricultural production since several decades ago. It includes classic image processing techniques that use different color spaces, as well as hyperspectral imaging, which can encompass near and far infrared, UV and X-rays. Apart from classic machine vision methods, the application of artificial neural networks and machine learning (especially deep learning) is currently causing considerable improvement in agricultural research and practice. In this paper, the principles of the selection of the different machine vision methods in different agricultural applications is considered. Special attention is paid to the examples of the applications of convolutional neural networks in sorting of agricultural products.**

Keywords—* *machine vision, sorting of agricultural products, machine learning component, formatting, style, styling, insert *(key words)*

I. INTRODUCTION

Machine vision is a branch of artificial intelligence. The first machine vision algorithms, such as edge detection and segmentation appeared in 1960's [1]. Edge detection, improved by Hough transform, was used by crop protection robots proposed in reference [2]. They used visual sensing to detect plant rows, as the navigation in the fields of cauliflowers, sugar beets and wheat. Applied algorithm successfully discriminated between plant, weed and soil.

Various digital technologies are used to reduce food waste and to mitigate losses in agricultural products (fruits, vegetables, grains) and to enhance food safety, both pre- and post-harvest i.e. in the whole food supply chain [3]. Artificial intelligence (AI) can speed up and improve the quality of the on-farm sorting and transportation, and reduces postharvest losses and mechanical injuries of products. Machine vision is used as an important support to precision agricultural, mostly plant, production [4]. It is multidisciplinary field because it requires expertise in optics, vision sensors, image processing and data science. Moreover, experts in all fields that use supervised machine learning image processing, are necessary for image labeling – ground truth. Machine vision has an important role in the introduction of smart agriculture [5] which can liberate the labor force and improves the quality and yield of crops.

Apart from assistance in plant protection robotic systems, in early 2000s optical, automatic sorting of agricultural products (fruits and vegetables) has been introduced into industrial plants. It is called color sorting which shows that the sorting was performed mostly according to the color of products. At that time, the main criteria for sorting relied on statistical properties of color in a digital image of agricultural product. Combining it with segmentation and pattern recognition improved the quality of sorting. The development of machine learning (ML) enabled the treatment of the statistical properties of the color (color features) in classification of products according to their color, shape and size. In the last decade simultaneously are rapidly developing both deep neural networks, as types of ML algorithms, and agricultural robots (agrobots [4]). It enables the automatization of many agricultural procedures, that used to be performed manually. Numerous approaches in this field are constantly emerging and developing. Nowadays, machine vision is involved in almost every aspect of agricultural production.

The aim of this paper is to review the application of machine vision in agricultural production in order to provide the help in the selection of machine vision systems in the field of agriculture. Section 2 presents image acquisition sensors used in agricultural research and practice. In the third section, main branches of image processing algorithms, including machine learning algorithms employed in the field are presented. Section 4 revises specific characteristics of the uses of machine vision in different plant production phases such as preharvest, harvest and postharvest. In the concluding section, some expected directions in the field development are specified.

II. IMAGE ACQUISITION SENSORS

Visible light cameras detect the intensity of visible light either in grayscale or in color. Frequently used imaging sensors are CCD and CMOS sensors. CCD and CMOS cameras have analog sensors (for each pixel analog value of intensity is recorded), therefore they give high resolution, high image quality and low noise. In commercial cameras, the signals from CCD and CMOS sensors are converted into digital signal. Nowadays, the most of the commercial cameras have CMOS sensors, due to their smaller dimensions and lower energy consumption. They usually record RGB images which are the most affordable nowadays.

RGB imaging is cheap and easily accessible and is included in ordinary cameras and mobile phone cameras. It is most widely employed in ripeness and volume estimation, color grading, surface damage detection, texture analysis, fruit counting for yield estimation, as well as disease detection on leaves and on fruits … because great majority of image processing algorithms and deep learning algorithms are developed just for RGB images [5]. The disadvantage of traditional RGB image processing is the fact that it is sensitive to illumination and lighting condition changes [6]. Those could be overcome by using deep learning algorithms. More information can be obtained by 3D RGB cameras or RGB depth cameras (RGBD), which, apart from red, green and blue matrices, also give the matrix of distances from the camera in greyscale. The depth information is acquired either using multiple (stereo) sensors, or time of flight measurement.

Apart from RGB color spaces, the other color spaces are also used for differentiating the images. One of them is hue-saturation-value color space (HSV) which is also called hue-saturation-intensity (HSI) [7, 8]. CIE L*a*b* color space – luminance, a: red / green axis, b: yellow / blue axis – is also one of the popular color spaces [9, 10, 11]. There are also several similar color spaces such as YCbCr, YUV and YPbPr – luminance, blue difference (or projection) and red difference (or projection), which are used in video and television signals, but can also be found in some agricultural applications [4].

Unlike the previously mentioned cameras, which register only visible light, multispectral cameras register radiation intensities in two or more spectrum bands that can belong to visible, infrared and ultraviolet wavelengths. Even more information can be obtained by hyperspectral cameras that register irradiation in continual wavelength range, usually in infrared or in visible and infrared range. Hyperspectral imaging (HSI) systems acquire spatial and spectral data that include wavelengths of visible light as well as wavelengths in infrared range. Images made for IR wavelengths can indicate even some internal defects of the products (internal decaying, dryness …), that are not visible on its surface. In HSI, full band irradiation can be recorded, or only certain number of distinct bands. HSI became popular in sorting [12, 13].

Near infrared hyperspectral imaging (NIR, 800nm – 1800nm) was used for nondestructive detection of codling moths in apples [14]. Short wavelength infrared (SWIR) hyperspectral imaging is used for apple grading [15]. Visible and near infrared (VNIR), in the range 673nm – 1100nm, is used to detect internal browning in mango [16], and 450nm – 1050nm range is used for defect grading in persimmon fruit [17]. The VNIR range of 400nm to 1000nm is used in classification of skin conditions in achacha fruit [18] and in damage detection of apple fruit [19]. Multispectral cameras images are more practical, cost effective and easier to process than continuous hyperspectral cameras. Multispectral high resolution satellite imagery is used for wheat on field disease monitoring [20]

X – ray radiography is also useful in internal defect detection. Recent report presented research on X – ray radiography for anomaly detection in apples and pears with the goal to be applied in online sorting [21]. It is also beneficial in bone and metal object detection, which is applied in food industry [22].

Less frequently, but also used in agricultural inspections are thermal cameras, which are particularly useful in detecting internal decays and rotten parts in extensive crop stocks. Magnetic resonance is suitable for fat content estimation [22]. Both techniques acquire images that can be treated by image processing techniques, and therefore belong to machine vision.

In general, the advantage of multispectral, hyperspectral, thermal cameras and X-ray imaging over regular color cameras is their ability to detect internal defects (internal bruises, decaying, dryness …, that cannot be noticed by standard visible light cameras. Their drawbacks are facts that they are expensive, require complex and time-consuming data processing techniques, produce large amount of data occupying significantly computer memory.

III. Image processing techniques

All sensing systems mentioned in previous section produce images according to which the decisions about taking certain agricultural measures and procedures should be made. In other words, obtained images should be treated by machine vision techniques, since the machine vision enables machines (computers) to make decisions according to images.

Traditionally, the first step in image processing is image segmentation [23, 24, 25]. The role of segmentation is to separate foreground and the background, by creating a mask, which enables the analysis of only those objects that are in the foreground. Segmented foreground can be leaves in phenotyping (Fig. 1) or growth monitoring, or fruits in ripeness monitoring and sorting. There are many ways to perform a segmentation, for example Otzu algorithm for grayscale image segmentation, gradient based segmentation etc. More recent are segmentation algorithms that use machine learning, such as unsupervised machine learning algorithm called k-means clustering [15]. This segmentation algorithm is used on Fig. 1a), as a result Fig. 1b) is obtained. Then, only the pixels inside the segmentation mask are analyzed.

In the early machine vision, segmentation is followed by the statistical analysis of the foreground. Numerous researches have been done in order to find which color properties are suitable for the discrimination between the acceptable and nonacceptable products [26, 27, 28]. Those properties could be average intensities of a color, its standard deviations, variances, minimum, maximum and median value of a color, and also higher color moments and statistical texture features. The goal is to measure the similarity of an image to a certain class of images, and to discard the objects dissimilar to the desired types of objects. Color intensity ratios [7, 9, 23] or band intensity ratios (in HIS processing) are also used to discriminate between the healthy leaves and the weed, or between the acceptable and unacceptable fruit or vegetable. There were many attempts to convert RGB color data into other color spaces and to use the components of other color spaces for discrimination. For example, hue component of the hue-saturation-value (HSV) color space was used for fruit grading [7].

a) b)

Fig. 1. Images used in phenotyping: a) raw image, b) segmented image

Conventional hyperspectral image (HSI) data analysis are band ratio (BR) and spectral angle mapper (SAM) [18]. BR calculates, (for each pixel position), the ratios of intensity values of two spectral bends, for all possible combinations of bands. Then, correlations between the band ratios and the labels are found, and 2-bend combination of maximum correlation is selected to be used for sorting, after the determination of optimum threshold (the value of intensity ratio that most efficiently differentiate between acceptable and defective products). It is used only for binary sorting. SAM takes images in n spectrum bands. Therefore, for each pixel, n-dimensional vector is created. Then, it calculates the n-dimensional angles between actual and referenced spectra. The referenced spectra were obtained by taking the average of the normalized spectra of each reference data class. A pixel is classified as a class with which the spectral vector of a pixel makes the smallest n-dimensional angle.

All those numerous statistical properties of color in an image, also called color features, are used as input variables of statistical machine learning algorithms. They can be supervised algorithms such as classification (binary or multiclass), or unsupervised such as clustering. In supervised machine learning, output variables are labels, which are annotated to the images. Set of pairs {image, label} represent a dataset, that is treated by machine learning algorithm. The dataset is divided in two parts: larger – training set on which the algorithm is trained, and smaller – test set on which the trained algorithm is evaluated. In some algorithms, training set is additionally divided into training and validation set

Machine learning (ML) tasks in machine vision include detecting the object on the image, annotating it with a label, finding the position of an object, and recognizing some specific traits of an object (useful in phenotyping, separating different ripeness stages, sorting …). Various ML algorithms include logistic regression, support vector machine (SVM), k nearest neighbors (kNN), decision tree and random forest algorithms [14, 15, 16, 19]. SVM is popular classification algorithm. It separates two classes of images using hyperplane. It can be extended to multiclass using one-vs-one, or one-vs-all approach. kNN annotate to a point the label equal to the label that the majority of k nearest neighbors in n-dimensional space has. N is the number of data features.

In machine learning of a perceptron type (logistic regression), vectors of parameters (weights and biases) are trained, using back propagation, on training set of data, with the goal of realizing the highest accuracy in classification of the test set data. An artificial neural network (ANN) consists of layers of nods ("neurons"): input layer, one or more hidden layers and output layer. If there are more than one hidden layer, the neural network is called deep neural network. The more layers are in the network, the deeper a neural network is. Hyperspectral images can also be treated by machine learning techniques, such as support vector machine (SVM) and artificial neural networks (ANN). In reference [18] ANN proved to give better accuracy (99,9%) then SVM (83.6%). In the same study the accuracy of SAM was 56%.

Further development of machine vision happened with the introduction of convolution operation, illustrated on Fig. 2. The application of convolution in machine learning resulted in convolutional neural networks (CNN) in which matrices of parameters in filters (kernels) are trained until the sufficient

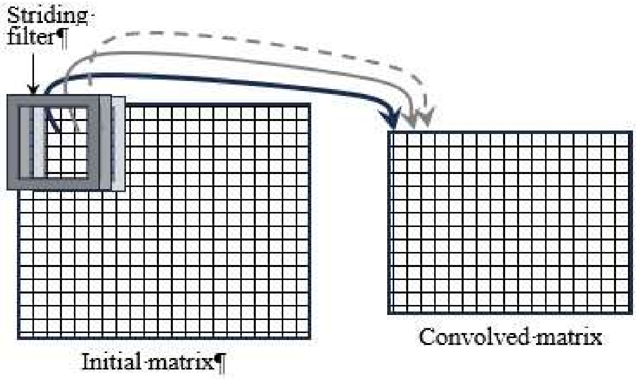

Fig. 2. The illustration of convolution process

accuracy in machine vision is achieved. The convolutional layer is usually followed by pooling layer, which is used to decrease the size of a matrix (image). In a standard CNN, after the input layer, there are several to many pairs of convolutional and pooling layers, which are usually followed by flatten layer (that converts matrices into vectors), and couple of fully connected, layers, or dense layers, before the output layer. Hyperparameters of neural networks are filter sizes, number of filters, pooling window sizes, pooling strides (step sizes) [29]. Researcher examine the variations of hyperparameters and variations of the deep learning neural network structure, trying to achieve better machine vision accuracy.

The improvements of CNNs are VGGNets, with two or more convolutional layers before each pooling layer (Fig. 3). VGGNet inspired the creation of ResNets (residual networks) – very deep networks, with improved performances (Fig.3). On the other hand, the different improvement of CNN led to R-CNN (region-based CNN). They afterwards evolved to Fast R-CNN and Faster R-CNN, which led, in 2016., to YOLO algorithms – real time object recognition algorithms [30, 31]. Its name is the abbreviation for "You Look Only Once". Firstly, they were used in autonomous vehicles [32, 33]. Currently, there is rapid development of the application of YOLO algorithm in many other fields including agriculture. Its application is reported for growth monitoring, in the case of orchard [34], and greenhouse [35]. Site specific weed management is done with weed detection in wheat field, performed with YOLO algorithm [36]. YOLOv3 version of the algorithm proved to be efficient in sorting (classification) of tomatoes [37], apples [38] and raspberries [39, 40].

And so on, different deep learning models are currently envisioned, created and tested by armies of engineering scientists all over the world with the goal of improvement of machine vision algorithms in various fields including agriculture.

In order to achieve efficient learning, it is desirable to supply large amount of input data for deep learning algorithms. Because of that, large image data bases are constantly created [41]. Also, many data augmentation strategies are developing. Some of them are simple transformations like rotation, bluring, the change of contrast, brightness and saturation in an image, noise introduction methods (Gaussian noise, speckle, salt and pepper noise), and some complex data augmentation methods (ORGNet, Mosaic, …).

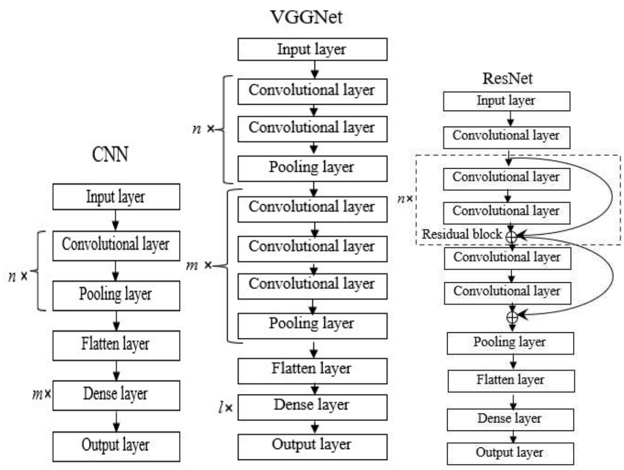

Fig. 3. Architecture of CNN, VGGNet and ResNet

IV. Phases of Agricultural Production That Use Machine Vision

All the applications of machine vision in agriculture can be divided in three phases: preharvest, harvest and postharvest applications. Since pre-sawing seed selection is important in agricultural research and production [42], techniques similar to machine vision sorting could be applied for it, though such reports were not found.

A. Preharvest

Preharvest activities include plant health monitoring, plant health protection, growth and ripeness monitoring [25]. All of them are tedious field tasks resulting in high labor cost. The concept of precise agriculture requires constant monitoring of items (plants or animals) and adequate decisions about the actions that will be taken. That action should be customized to each plant or animal needs. For example, nutritional deficiencies (lack of Ca, K, Fe …) can be detected with machine vision systema, according to the color and texture of the leaves. The ripeness monitoring involves differentiating the ripeness levels and estimating the percent of ripe fruits in the field, or estimating the percent of fruits that belong to each ripeness level.

In a similar way like the machine vision is used in industrial inspection, furniture manufacturing and autonomous vehicles, it is also used in monitoring and inspection of crops in the phase of growth and ripening, replacing that way the traditional manual, which requires a lot of manpower.

The diversity of crop growing environments, such as fields, orchards and greenhouses require the development of different machine vision systems, while the flexible machine vision systems are still to be developed.

On-site cameras (fixed position cameras) and cameras on the ground robots or drones are used for growth stage identification and crop yield estimation. For leaf detection and lief area calculation, simple statistic values for green color on images can be used. The similar holds for the bud and flower detection as well as for the ripeness monitoring, only the percent of another color is measured.

Pest, weed, fungi and other disease detection and identification is of great importance since those infestations can quickly spread from infested plants to neighboring healthy plants, which leads to significant reduction in yield. Machine vision enables site specific treatment that is to say it enables precise pesticide or herbicide treatment – the treatment of only infested regions and not the whole field, saving that way the treatment chemicals and maintaining the overall healthiness of the products.

B. Harvest

The development of harvesting robots is different for different crops. High harvesting efficiency is achieved with picking robots for larger size products such as apples, lemons and tomatoes [4, 5, 7]. Special attention is paid to the developments of robots for the harvesting of labor-intensive crops, such as strawberries [5].

Currently, picking robots are still less efficient [5] than manual picking. They often damage branches and fruits (break fruit skin). There are intensive efforts in the development of picking robots, the important part of which is machine vision.

There are several types of picking systems that use machine vision. The most developed are picking devices with ground mobile platforms, whereas drone or quadcopter picking techniques are still in development phase.

The fruit harvesting device consists of mechanical parts and electronic parts. Mechanical parts are an autonomous mobile platform, mechanical arm and end effectors (pincers or grippers). Electronic parts are machine vision sensor system and decision-making processor.

Multi-sensor machine vision system is very important for the picking efficiency. It recognizes the fruit and detects its position, including the distance measurement which is done by 3D imaging sensors or laser devices (lidars or visual servo laser directional ranging coupled with the robotic arm). The accuracy of this process is significantly affected by the complexity of crop growing environment, that includes branches, leaves, neighboring fruits, light and shade distribution.

An intelligent decision-making system is responsible for optimum performance of multi degree of freedom robotic arm. Its tasks are robotic arm path planning and obstacle avoidance. This decision-making system realizes the communication between the machine vision system and the robotic arm. Both of them are important for gripping success rate. Some successful realizations of picking robots are reported in [8] for tea flowers, in [7] and [28] for citrus fruits.

C. Postharvest

Main postharvest activities, supported by machine vision, are sorting and food stock monitoring. Sorting presents classification of harvested products. The quality of sorting affects the commercialization of agricultural products. Traditionally, the sorting of agricultural products has been performed manually, but this method is subjective, affected by the eye fatigue and therefore inconsistent. When the production is considerably large, manual sorting requires great number of workers and might be slow, and unsuitable. The advantages of machine vision are the facts that it is non-invasive and fast.

Sorting consists of two phases: sorting out defective products (damaged, diseased, rotten, over-ripe…), and separating the acceptable products according to quality, ripeness, color, size, shape and color consistency.

Sorting lines are parts of factory integrated production lines. They use the combination of industrial camera imaging with flipping mechanisms in order to achieve complete product surface inspection [16] There are also machine vision systems in on-farm sorting in the fields and orchards of small farms.

Machine vision in commercial sorting of agricultural products uses RGB images. Color statistics of the product with a defect can be similar to that of the normal skin. Therefore, some defects can be misclassified as normal skin due to the similarities of their color (statistics). Water drops, or rain spots can be classified as skars. Particular task in machine vision sorting is to prevent stem ends to be misclassified as defects. The solution of that task includes masking, finding the center of a fruit, pattern recognition and decision-making techniques. All those problems could be overcome with adequately trained advanced deep neural networks (ResNet or YOLO).

During stocking period, products (fruits) with defects can cause severe consequences if left undetected during the post-harvest processing. Therefore, it is important to classify fruits with insect infested skin, or the appearance of fungi.

There are two main types of sorting – binary classification and multiclass classification. In binary classification, dummy variable 0 represents the acceptable product (fruit), and 1 represents unacceptable product (various defective classes can be merged into that class). The system that is capable for multiclass classification can also be applied for binary classification.

Finally, machine vision is important in food quality inspection, such as assessment of meat, fish, fruits, vegetables and grains [22].

V. Conclusion

Increasing the number and the diversity of dataset samples, especially open-source data sets samples will improve learning efficiency of deep learning algorithms.

Further developments of deep learning algorithms are aimed at the increase of the detection, classification and positioning accuracy, as well as at reduction of the processing time and computer memory occupation.

Improving the dynamic monitoring mode, for example recognizing and positioning the waving fruits, is still unsolved task.

Today, there is a problem of lack of the universality of machine vision models – they are usually developed for only one crop type. Generalization of models in order to be used for different crops is another challenging task.

Rapid development of image acquisition devices, and image processing techniques, particularly the development of deep learning, guarantee significant improvement of agricultural production.

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Apstrakt – Mašinski vid je uključen u istraživanja i praktičnu primenu različitih faza u poljoprivrednoj proizvodnji poslednjih nekoliko decenija. Ta primena uključuje korišćenje klasičnih tehnika za obradu slike, korišćenjem različitih prostora boje, kao i hiperspektralnog snimanja, koja mogu obuhvatiti bliske i dalje infracrvene, ultraljubičaste i X-zrake. Pored klasičnih metoda mašinskog vida, primena veštačkih neuralnih mreža i mašinskog učenja (pogotovu dubokog učenja) trenutno prouzrokuje značajno poboljšanje u istraživanjima u poljoprivredi i u poljoprivrednoj praksi. U ovom radu su razmatrani principi izbora raznovrsnih metoda mašinskog vida u različitim primenama u poljoprivredi. Posebna pažnja je posvećena primerima primena konvolucionih neuralnih mreža u prebiranju poljoprivrednih proizvoda.

Ključne reči: mašinski vid, prebiranje poljoprivrednih proizvoda, mašinsko učenje.