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IMAGE ANALYSIS AND NEURAL NETWORKS IN THE PROCESS OF IDENTIFYING OF SELECTED MECHANICAL DAMAGE TO MAIZE CARYOPSES

Summary

The subject of the project was to develop a neural model for the identification of selected mechanical damage to maize caryopses on the basis of digital photographs. The author has selected a set of features that distinguish damaged and healthy caryopses. As a result of this study it has been obtained an artificial neural network of a multilayer perceptron type whose identification capacity is near of the human's one.

NEURONOWA ANALIZA OBRAZU W PROCESIE IDENTYFIKACJI MECHANICZNYCH USZKODZEŃ WYBRANYCH ZIARNIAKÓW KUKURYDZY

Streszczenie

Celem projektu badawczego było opracowanie modelu neuronowego do identyfikacji mechanicznych uszkodzeń ziarniaków kukurydzy na podstawie ich cyfrowych fotografii. Wybrany został zestaw cech charakterystycznych na podstawie, których możliwa jest klasyfikacja ziarniaków na zdrowe i uszkodzone. W wyniku badań otrzymano sztuczną sieć neuronową typu perceptron wielowarstwowy charakteryzującą się zdolnościami identyfikacyjnymi zbliżonymi do umiejętności człowieka.

1. Introduction

Finding high quality plant materials and producing safe food has become a research priority in the European Union. In order to ensure highest quality, the level of impurities must be minimised. One form of impurities are damaged caryopses. The primary purpose in assessing the number of mechanically damaged caryopses is to gauge the quality of cereal grains. The secondary goal is to evaluate applied agricultural techniques. A complete record of the production process offers insights into the nature of damage and where it occurs. So far, identification has been limited largely to having human sighters spot damaged grains visually. An alternative is a set of screens that separate damaged and healthy caryopses. The screens provide data on the number of damaged grains but not on the nature of damage. The author has sought to identify damaged maize caryopses by means of computer-aided image analysis and an artificial neural network.

2. Literature overview

Grain damage erodes market value cutting into producer income. It is therefore essential to develop affordable and effective means of identifying such damage. In agricultural terminology, grain damage falls under the definition of grain impurities [5]. Hence, the practice is not to recognize grain damage as a separate phenomenon. Industrial facilities commonly rely on mechanical screen sets to separate damaged and healthy grains. Damage to caryopses in samples is then assessed manually. Assessments take approximately a minute per caryopsis. Yet, given the long time required to identify damaged grains, assessments must be limited to single sample checks from each batch. Hence, efforts are under way to bring machine-identification of grain damage to the human quality standard allowing testing greater quantities of crops at the same time. Niewczas attempted to evaluate mechanical damage to wheat caryopses using X-ray techniques. The images were used to acquire information on the severity and nature of damage. Unfortunately, the method has proven to be poorly suited for industrial use. The cost of X-ray photography and the conditions required therefor limit the method to laboratory applications [3]. The use of thermography to identify the quality parameters of selected cereal and fruit grains, as described by Baranowski, entailed measurements of the radiation temperature on surfaces of selected cereal and fruit grains as well as the assessment of the suitability of such measurements for determining quality of the tested objects. Baranowski performed over a dozen sets of measurements of radiation temperature on the surfaces of the wheat, rye and maize grains and found substantial temperature differences between damaged and undamaged grains. The method may be of practical use in evaluating the proportion of damaged grains in total yield [1]. The above research work has sought to apply a range of technologies to identify and assess macrodamage in cereal grains. However, none of the methods has been adopted by the industry. None has succeeded in offering a way of identifying grain damage at an efficiency level comparable to that of human operators. The advantage of humans lies in their ability to perceive and draw conclusions on the recorded image. As of to date, no machine identification method has employed a similar mechanism. It thus seems advisable to devise a mechanical identification system that relies on image analysis and artificial neural networks which are actually equivalent to the mechanism that humans employ in such identification.

3. Materials and methods

The author procured biological material in the form of maize caryopses of the Clarica FAO 280 variety. Two study samples were taken, containing 100 and 50 caryopses respectively. One of them contained 16 mechanically damaged caryopses out of the total of 100, the other: 6 out of 50. The images were obtained with the use of a station made up of a light tent, camera tripod, digital (reflex) camera and a set of lights. Each caryopsis was photographed three times, each time being turned by 180° so as to expose its entire surface. After that they were exported to a bitmap (*.bmb) format. The key stage was to select those caryopsis features that will allow the artificial neural network to identify damage. The author chose a set of representative variables that included a set of features providing information on colour relying on the RGB colour space model coded in a proprietary manner, and a selection of features containing information on shape as described with the use of selected shape coefficients:

a) undimension coefficient

$$R_s = \frac{L^2}{4\pi \cdot S}, \tag{1}$$

where: L – circuit, S – field;

b) *Feret* coefficient

$$R_F = \frac{|L_n}{L_v}, \tag{2}$$

where:
L_N – maximum vertical size,
L_V – maximum horizontal size;

c) first circuit coefficients

$$R_{C1} = 2\sqrt{\frac{S}{\pi}}; \tag{3}$$

d) second circuit coefficients

$$R_{C2} = \frac{L}{\pi}; \tag{4}$$

e) *Malinowska* coefficient

$$R_m = \frac{L}{2\sqrt{\pi \cdot S}}. \tag{5}$$

Given the enormous quantity of data from a single photoghraph and the limitations of the artificial neural network simulator, the author chose to divide the images into standardized fragments. The author tested two image fragment sizes of 32 x 32 and 16 x 16 pixels. The optimal photograph size, as established by tests, turned out to be 512x512 pixels. Information on the structure of the learning sets is provided in Table 1.

Tab. 1. Information about structure of learning files

Number of learning files	Image size (pixels)	Fragment size (pixel)	Size of single learning example	Number of examples
1	256x256	16x16	263	9200
2	256x256	32x32	1031	3702
3	512x512	16x16	263	9216
4	512x512	32x32	1031	3072
5	512x512	16x16	263	1952
6	512x512	32x32	1031	3200

To make effective use of the caryopsis macrodamage data derived from the photographs, one needs to convert the graphical data into learning sets designed to support the learning of artificial neural networks. To that end, the author developed a special information system (Figure 1).

Once the image has been converted and analyzed, the system records selected information in a learning set format suited for the artificial neural network. The data set is divided into learning test and validation subsets. The available network typologies selected for test purposes were a linear network, a radial base function network, probabilistic neural networks, a general regression neural networks, a three-layered (one hidden layer) MLP network, and a four-layered (two hidden layers) MLP network [4]. The topologies and learning methods for the tested models are shown in Table 2.

During the network learning stage, mechanical damage to maize caryopses was best identified by the single-hidden-layer MLP network. This may be owed to the dual nature of the identification task. Learning relied on the backpropagation of errors at the first stage and on the conjugate gradient method in the second stage. The learning parameters turned out to be significantly better for networks using data from larger image fragments (32 x 32 pixels).

Fig. 1. Information system for creating learning files from images: schema of working

Tab. 2. Information about topology and learning methods of neural models

Number of model	Number of enters and topology	Number of neurons in hidden layer	Number of exits	Learning methods
1	263 MLP	26	1	*BP*50**CG*168*
2	1031 MLP	33	1	*BP*50**CG*165*
3	263 MLP	29	1	*BP*50*CG217*
4	1031 MLP	41	1	*BP*50*CG255*
5	263 MLP	43	1	*BP*50**CG*173*
6	1031 MLP	33	1	*BP*50**CG*289*

* – number of learning epochs, BP – Back Propagation, CG – Conjugate Gradient

4. Results

The network that best identifies the mechanical damage of caryopses was selected by means of the results of the learning, validation and testing sets. The author assessed individual model features such as the rate of learning, validation and test errors, the learning, validation and testing related quality of the neural network, the Receiver Operating Characteristic curve and classification problem statistics [6]. Statistics of model that best identified damage:

- learning error – 0,1069,
- validation error – 0,1371,
- test error – 0,1384,
- learning quality – 0,9907,
- validation quality – 0,9785,
- test quality - 0,9718,
- filed under ROC curve – 0,9713,
- classification problem statistics – on 1000, 27 was bad classified.

The model that best identified damage was designed on the basis of a multilayer (single hidden layer) perceptron artificial neural network with 263 inputs, an output and 43 neurons in the hidden layer. The network was taught over 50 epochs by way of backpropagation of errors and over 173 epochs by way of conjugate gradients.

5. Conclusions

The studies suggest that it is advisable to apply the artificial neural network technology and computer-aided image analysis to identify damage. This conclusion is further supported by satisfactory characteristics of the best performing identification model. The study also revealed the optimal size of the caryopsis image to be used for the preparing of teaching sets for artificial neural networks. It is a compromise between image resolution and the size of the learning case which is limited by the processing power of the artificial neural network simulator. The approximate average global error rate of the top model is 8%. The approximate average error rate of humans in damage classification is 3% [2]. Hence, the identification quality of the neural model is inferior to that of a man. On the other hand, neural networks' definite advantage over man is their speed and identification repeatability. The model is capable for identifying a much larger number of caryopses than a human sighter. The only constraint on the number lies in limitations of image acquisition and the processing power of the hardware. Another strong advantage lies in the absence of natural limitations that confine humans. A neural model can work continuously as it e.g. does not succumb to fatigue.

The neural model developed and verified by the authors demonstrates that it is advisable to apply it to identify macrodamage in maize caryopses based on representative features established in caryopsis image analysis

6. References

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