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NEURAL IMAGE ANALYSIS IN IDENTIFICATION PROCESS OF MECHANICAL DAMAGES OF KERNELS

Summary

The subject of the study was to develop a neural model for the identification of mechanical damage in maize caryopses based on digital photographs. The author has selected a set of features that distinguish between damaged and healthy caryopses. The study has produced an artificial neural network of a multilayer perceptron type whose identification capacity approximates that of a human.

NEURONOWA ANALIZA OBRAZU W PROCESIE IDENTYFIKACJI MECHANICZNYCH USZKODZEŃ ZIARNIAKÓW

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 and literature review

The recent overproduction of agricultural products has brought substantial pressures to bear on the quality of goods placed on the market. Finding high quality plant materials and producing safe food has become a research priority in the European Union. Quality testing of cereal grains is a highly complex multi-stage process. In order to ensure highest quality, the level of impurities must be minimised. One form of impurities are damaged kernels. The primary purpose in assessing the number of mechanically damaged kernels 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 kernels. 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 kernels by means of computer-aided image analysis and an artificial neural network. Of all damage types, focus was placed on mechanical macrodamage. Cereal grain damage has a strong impact on the quality and volume of yield. 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 kernels in samples is then assessed manually. Assessments take approximately a minute per caryopsis. A well-trained specialist can distinguish damaged and healthy kernels with 100% certainty. 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 in wheat kernels 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]. Another option is to measure the velocity of acoustic waves to identify mechanical damage in cereal grains. The method, as researched by *Stasiak*, has failed to fulfill expectations. Efforts continue to improve it [6]. *Zdunek,* in his turn, attempted to apply acoustic emissions to detect plant tissue ruptures. While his work did not focus on identifying grain damage, it could be used in assessing the quantities of damaged grains in yield [8]. 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

2. Materials and methods

To conduct the project, as described above, the author procured biological material in the form of maize kernels of the Clarica FAO 280 variety. Two study samples were taken, containing 100 and 50 kernels respectively. One of them contained 16 mechanically damaged kernels 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 placed in the tent against a black backdrop and photographed three times, each time being turned by 180° so as to expose its entire surface. Prior to their conversion to learning sets, all photographs were processed to improve image parameters such as sharpness and contrast and, where needed, to frame them appropriately. 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 32x32 and 16x16 pixels (Figure 1).

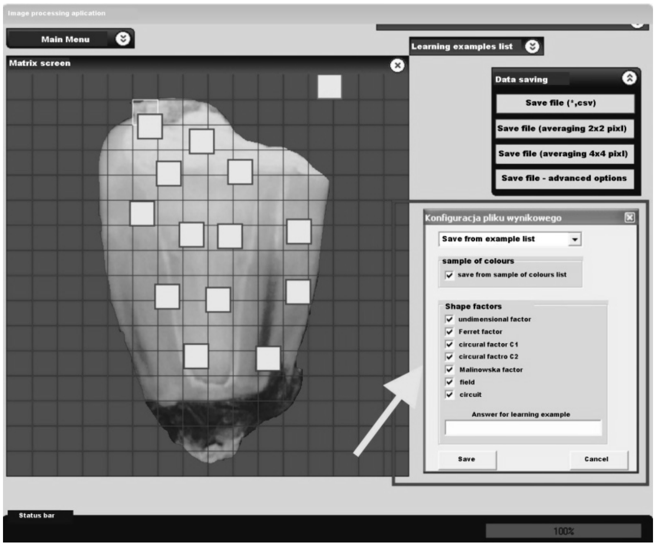

Fig. 1. Information system for image analysis – choice of learning data

Table 1. Information about structure of learning files

Symbol of learning files	Image size (pixels)	Fragment size (pixel)	Size of single learning example	Number of examples	Number of learning examples	Number of validation examples	Number of testing examples
α	256x256	16x16	263	9200	4600	2300	2300
β	256x256	32x32	1031	3702	1852	925	925
γ	512x512	16x16	263	9216	4608	2304	2304
δ	512x512	32x32	1031	3072	1536	768	768
ε	512x512	16x16	263	1952	976	488	488

ζ	512x512	32x32	1031	3200	1600	800	800

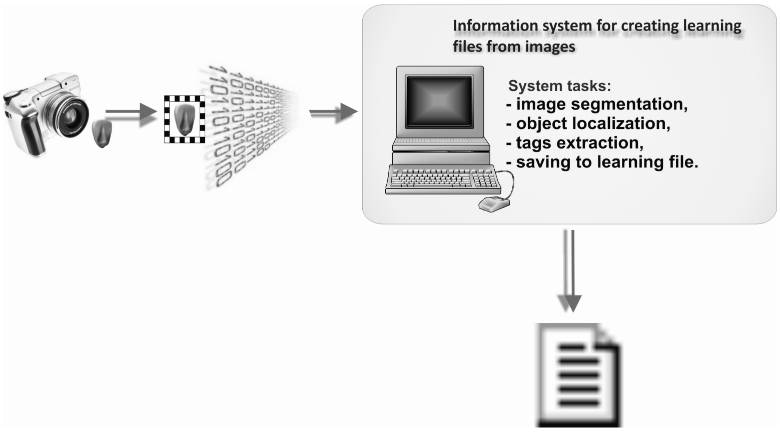

Figure 2. Information system for creating learning files from images - schema of working

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

Number of model	Symbol of learning files	Type of network	Number of enters	Nmuber of neurons In hiden layer	Number of exits	Learning methods
1	α	*MLP*	263	26	1	*BP*50**CG*168*
2	β	*MLP*	1031	33	1	*BP*50**CG*165*
3	γ	*MLP*	263	29	1	*BP*50*CG217*
4	δ	*MLP*	1031	41	1	*BP*50*CG255*
5	ε	*MLP*	263	43	1	*BP*50**CG*173*
6	ζ	*MLP*	1031	33	1	*BP*50**CG*289*

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

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. 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 2). 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 kernels 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 (32x32 pixels).

3. Results

The network that best identifies the mechanical damage of kernels 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 [7].

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.

4. Conclusions

The studies suggest 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% which means that 8 out of 100 kernels end up being misclassified. Comparisons show that human identification capacity is far superior. The approximate average error rate of humans in damage classification is 3% (materials of the Agricultural Market Agency 2005). 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 of identifying a much larger number of kernels than a human sighter. The only constraint on the number lies in limitations of image acquisition and the processing power of the hardware on which the model is run. 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. It is not perfectly fit for tasks where the highest quality of identification is essential, e.g. laboratory testing. It will, however, serve its purpose well wherever identification time and process continuity are critical, as in such practical applications as grain sorting.

The neural model developed and verified by the author demonstrates it is advisable to apply it to identify macrodamage in maize kernels based on representative features established in caryopsis image analysis. In practical applications, the model has proven superior to the identification capacities of man, in particular where identification speed and duplicability are of the essence.

5. References

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