A QUALITY SORTING METHOD FOR 'JONAGOLD' APPLES

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INTRODUCTION

Computer vision based automatic quality sorting of apple fruits is a hard but necessary task for increasing the speed of sorting as well as eliminating the human error in the process. In this field Leemans (Leemans and Destain, 2004) used a hierarchical grading method and k-means clustering for a real-time grading system where he reached 73% correct classification. Wen (Wen and Tao, 1999) introduced a rule-based apple sorting system and reached high recognition rates, but misclassified stem-ends and calyxes as defected areas. Nakano used two neural networks for color grading of 'San Fuji' apples, where he reached classification rate of 75 % for damaged fruits (Nakano, 1997). Li introduced a computer vision based system to grade apples, where defects are segmented by subtraction of a reference image from original, stem-end / calyx areas are identified by an artificial neural network and then fruit is graded according to its total defect area (Li et al., 2002).

Segmentation of skin defects of apple fruits is one of the major problems of this field where research still continues to accurately segment and identify these defects. In order to segment defects on apples, Leemans introduced a Gaussian model of skin color to segment defects on 'Golden Delicious' apples, where detection was effective but healthy skin presenting patches was segmented as defected (Leemans et al., 1998). Leemans also introduced a defect segmentation method based on Bayesian classification for 'Jonagold' apples, where segmentation of russet defects and color transition areas of skin were problematic (Leemans et al., 1999). Rennick used a controlled acquisition system and different classifiers to classify skin color and detect blemishes of 'Granny Smith' apples (Rennick et al., 1999). Yang introduced an automatic system to detect patch-like defects on apples by computer vision, where he used flooding algorithm to segment defects, structural light and neural networks to find stem-ends and calyxes and snakes algorithm to refine defected area (Yang, 1995). Unay introduced a neural network based system to segment defects on 'Jonagold' apples, where misclassifications occurred at the edges of the fruit skin (Unay and Gosselin, 2004).

In this research, 'Jonagold' apples (bi-colored skin) with defects of varying size and types have to be classified to pre-determined categories as correctly and as quick as possible (+10 apples/sec). For this purpose, an artificial neural network based automatic quality sorting approach for apples is introduced in this paper.

METHODOLOGY

The diagram of our defect segmentation approach can be seen in Figure 1. Our approach works as follows: Images of a fruit is introduced to the system. Fruit area is extracted from the background by pre-processing. Attributes of each pixel of fruit are extracted and introduced to the artificial neural network, which classified them into one of the 'healthy', 'defected' or 'stem-end/calyx' classes. Then, post-processing is applied on these results to remove very small defected regions. Finally, the fruit is assigned to one of two classes by the area of its defect.

AgEng Leuven 2004 – Engineering the Future
(International Conference of Agricultural Engineering)
12-16 September 2004, Leuven, Belgium

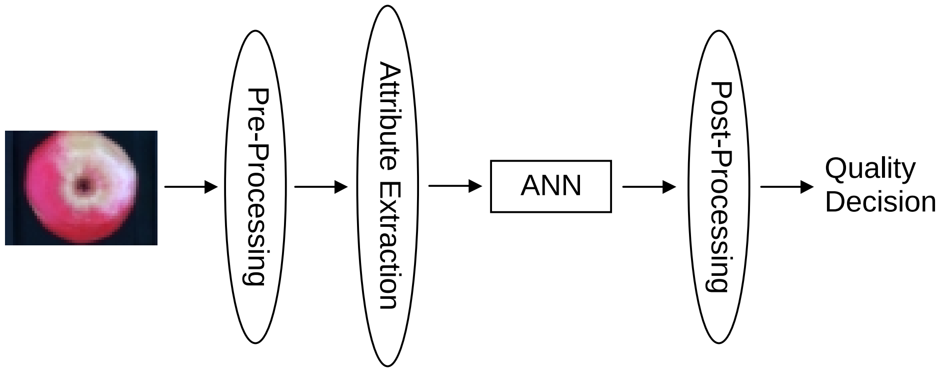


Figure 1. Scheme of our defect segmentation approach.

Image Database
Database consists of one-view images of 819 'Jonagold' apples taken from diffusely illuminated environment by a ccd-camera with four band-pass filters centered at 450, 500, 750, and 800 nm with bandwidths of 80, 40, 80, and 50 nm, respectively. 280 of these fruits were healthy whereas 246 of them included several skin defects (russet, scald, hail damage, limb rub, scar tissue, frost damage, rot, flesh damage and recent bruises) in varying size and shapes. Rest of the database was composed of stem-end, calyx views of several apples. For details of the image acquisition system, please refer to the work of Kleynen (Kleynen et al., 2003).

Defected and stem-end/calyx regions on the images of the database are manually segmented by O. Kleynen and D. Unay, respectively, and they are used as reference for comparison in this work.

Pre-Processing
Images of fruits are taken on a dark-colored background and observations revealed that fruit area could be easily isolated from the background by thresholding and morphological filling operations applied on the image of 800nm filter. This concludes our pre-processing step.

Attribute Extraction
As segmentation of defects is proposed at pixel level, for each pixel of the fruit its intensity values from four filters are used as local attributes. In addition to the local attributes, average and standard deviation of intensity values of the fruit are also calculated for each filter image, making up the global attributes. Therefore, each pixel is represented to the classifier by 12 attributes.
In order to train the classifier, equal number of pixels from healthy, defected, and stem-end/calyx tissue is randomly selected by the help of reference images. The attributes of these pixels form the training dataset. As the size of our database is small, attributes of pixels of the fruit being tested are excluded from the training dataset to permit results closer to reality.

Artificial Neural Network
After pre-processing and attribute extraction steps, pixels of the fruit are introduced to the artificial neural network (ANN). It is a 2-layer, back-propagated network of perceptron neurons. It has an adaptive learning rate and it uses cross-validation technique, i.e. in the training step it splits the training dataset into two non-overlapping

parts, ¾ of it for training and ¼ of it for validation. The following results are obtained by an ANN with 5 neurons in the hidden layer.

Post-Processing

In order to refine the result of ANN for each fruit, post-processing step is applied as follows: Connected components search with 8-neighbors is applied on the results of ANN that are assigned as defect. Connected objects (results of connected components search) having area smaller than a threshold are re-classified as healthy.

Quality Sorting

According to the common marketing standard of European Commission, apples are divided into four quality classes with respect to skin quality, color, fruit shape and size (Anonymous, 2001). When taking into account only the fruit size and skin quality (i.e. existence of skin defects), skin defects must not extend over 2.5cm^2 in area and minimum diameter of the fruit should be 65 mm for an apple to be regarded as healthy. These limit values permit us to define '*defect-decision ratio*', which was introduced by the authors before but was erroneous (Unay and Gosselin, 2004), as ratio of total defected skin to the total surface area of fruit. '*Defect-decision ratio*' calculated with the above limit values will provide us a binary quality sorting problem where fruits with ratio less than 0.07534 will be assigned to 'accepted' class and those with higher ratio will be assigned to 'rejected'. Equation 1 shows the formula and calculated value of '*defect-decision ratio*', where *A* and *d* refer to area and diameter, respectively.

$$r = \frac{A_{defected}}{A_{fruit}} = \frac{A_{defected}}{\pi\left(\frac{d}{2}\right)^2} = \frac{2.5cm^2}{\pi\left(\frac{65mm}{2}\right)^2} \approx 0.07534 \qquad \text{Eq. 1}$$

Our database is divided into two classes with the above '*defect-decision ratio*', where there are 119 and 700 fruits in 'rejected' and 'accepted' classes, respectively. It should be noted that this classification does not take into account types of defects, skin color or fruit shape, which are necessary for a more accurate grading. However, it can provide us important information for the next step of this research; grading apples by defect types.

RESULTS

In our previous paper it was shown that automatic segmentation of skin defects of apples with artificial neural network is more effective if the classifier is trained to find 'healthy', 'defected' and 'stem-end/calyx' tissue, than just 'healthy' and 'defected' ones (Unay and Gosselin, 2004). An example of this automatic segmentation can be seen in Figure 2.

Our observations on the results of automatic segmentations revealed that sometimes healthy tissue closer to the edge of fruits were misclassified as defected, which is probably due to the illumination artifacts related to the varying slope of fruit surface relative to camera. In order to eliminate such misclassifications, for each pixel a new attribute related to pixels' location relative to the fruit's center is also introduced to the ANN. First geometric center of fruit is found, then distance of each pixel from the center is calculated and lastly, they are normalized to fall in the range of [0,1]. The new attribute is inversely related to this normalized relative distance value and is named as '*altered distance*' (ρ). Different approaches of '*altered distance*' attribute are tested with the system. Figure 3 shows graphical illustrations of these approaches.

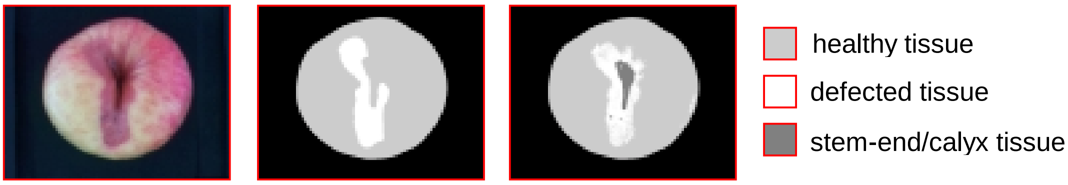


Figure 2: An example of automatic defect segmentation without post-processing. Left to right: original (rgb), reference and segmented images. Legend of synthetic images is on the far right.

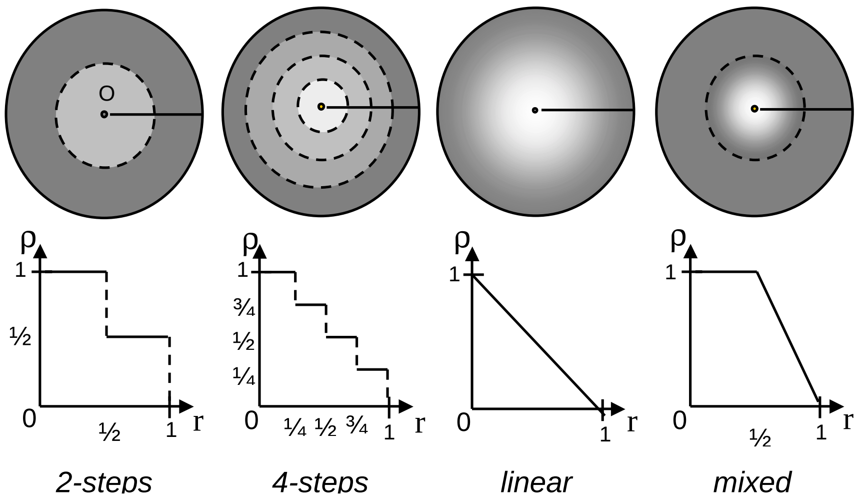


Figure 3: Different approaches of '*altered distance*' attribute. Graphics below show the relation between relative distance of pixels and their '*altered distance*' value. Figures on the top represent the fruit area quantized with respect to the approach.

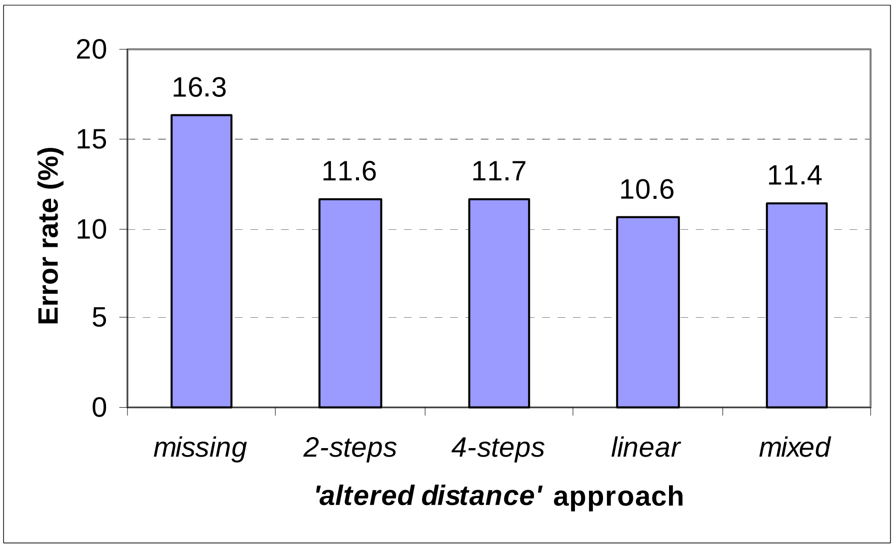


Figure 4: Average classification errors of different '*altered distance*' approaches. For comparison, error of the system without '*altered distance*' attribute is also displayed ('*missing*').

Automatic defect segmentation is repeated with each '*altered distance*' approach for the whole database and average classification errors are displayed in Figure 4. '*Missing*' approach, which is displayed for comparison, refers to the average error rate of segmentation without the '*altered distance*' attribute. Average error rates show that introducing the '*altered distance*' attribute significantly decreases misclassifications by about 5%. Furthermore, the lowest error rate, 10.6%, is observed with the '*linear*' approach.

Artificial neural network is a probabilistic classifier that assigns samples to classes according its learning process. When a test sample is introduced, it calculates a score value from the attributes and assigns the sample to a class by its score (e.g. binary problem: sample with score inferior to 0.5 is assigned to Class A, else to Class B). Using rejection rate with ANN is the same as introducing an uncertainty region in its classification space. Therefore test samples that do not have significantly high scores are left unclassified (rejected), rather than random assignment (e.g. binary problem. Samples with score superior to 0.6 are assigned, but those with score inferior to 0.6 are rejected). Several rates of rejection are introduced to the ANN and average classification errors of the system over the database are observed. Figure 5 displays results of these tests with average percentage of rejected pixels per fruit in horizontal axis and related error rates in vertical one. As observed, classification error strictly decreases from 11% to 3% as percentage of rejection increases, which proves the necessity of rejection. However, a very high rejection rate may reject too many pixels of fruit skin (those of defected tissue also), and therefore may not discriminate between defect types. So, an optimum point of rejection rate should be searched with an evaluation step that takes into account not only defect size but also defect types.

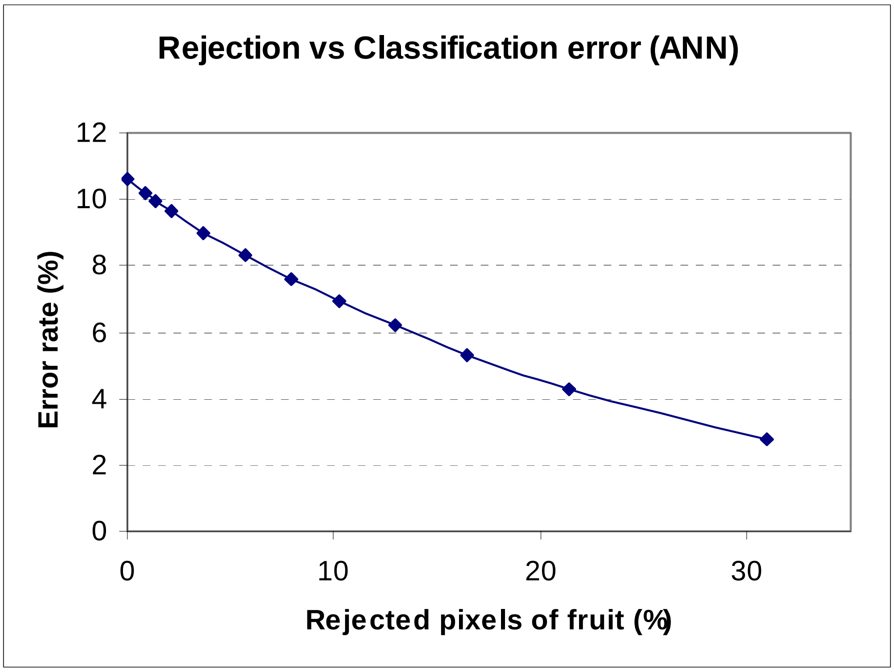


Figure 5: Effect of rejection rate of ANN on classification error. Percentage of rejected pixels of fruit displayed in horizontal axis and percentage of classification error in vertical axis.

Visual improvement of post-processing (threshold at 50 pixels) on defect segmentation was already shown (Unay and Gosselin, 2004). In this paper, we introduce segmentation errors of the system when different threshold values are used in post-processing step. Figure 6 displays average error rates with respect to threshold values. As post-processing step is applied only on the defected pixels of ANN output, the results in the figure are only from the images of the database that contain defects. Figure 6 indicates that average error shows a slight decrease first (up to 100 pixels threshold), and then starts increasing. Using a threshold value higher that 1000 pixels degrades the segmentation. Our observations show that, high thresholds of post-processing degrade defect segmentation, but also eliminate false segmentations for fruits, which do not have defect actually. So, search of an optimum value for post-processing threshold is necessary and it will be done with an evaluation step that takes into account not only defect size but also defect types.

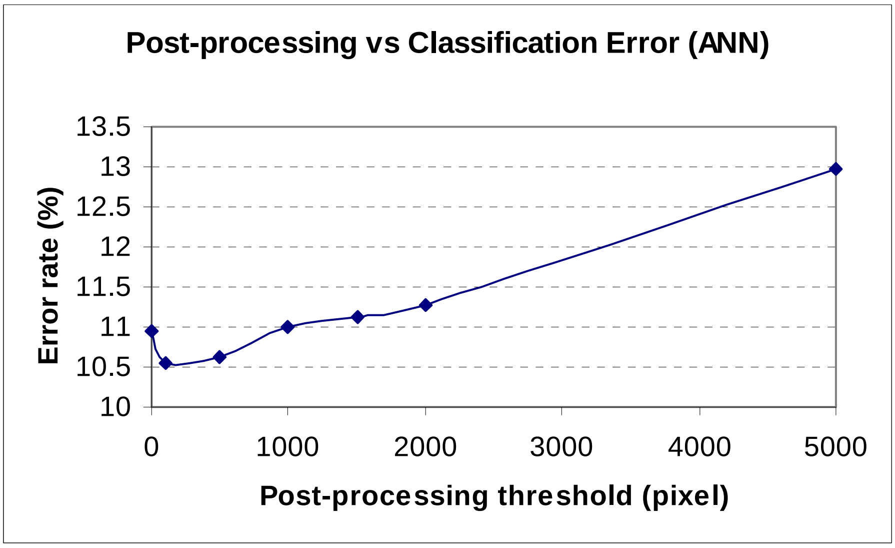


Figure 6: Effect of post-processing on classification error. Threshold value of post-processing displayed in horizontal axis and percentage of classification error in vertical axis.

Using the quality sorting approach introduced in the *Methodology* section, several tests are done to find the optimum performance of our proposed system, which depends on many parameters like complexity (number of hidden nodes and layers) and rejection rate of the ANN as well as the threshold of post-processing step, among others. Confusion matrix of one of these several tests is displayed in Table 1. Percentage of correct classifications are higher than 80% for each class and the global classification reaches to 82 %, which are below the tolerances of standards of European Commission, but encouraging.

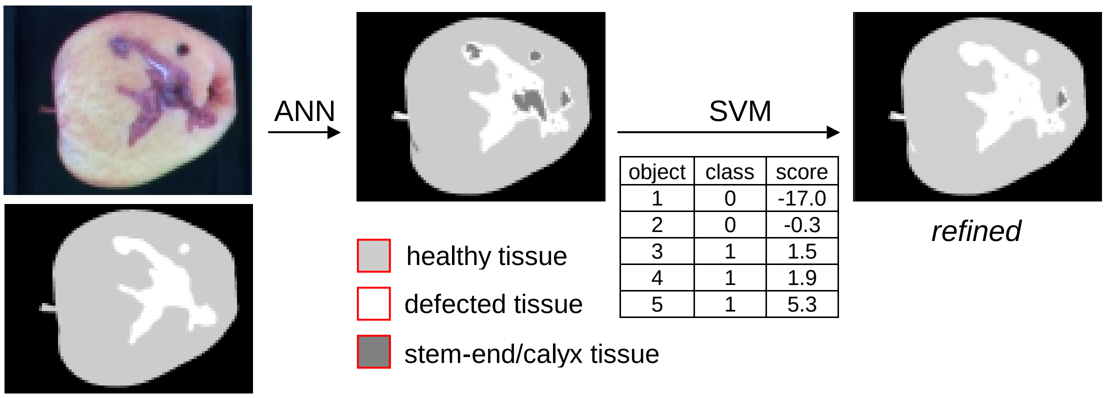
	true classes	
graded in	Accepted	Rejected
Accepted	563	10
Rejected	137	109
correct %	80.43	91.60
global correct %	82.05	

Table 1. Confusion matrix over the database

Computation time for defect segmentation of ANN classifier (13 input, 5 hidden and 3 output neurons) was 450 ms per view with original images (430x560 pixels, 8 bits). If image size is reduced to 128x128 pixels, 8 bits (about 14.7 times reduction in size), then computation time decreases to 40 ms per view, which will permit us to inspect 5 fruits per second with 4 different views. These tests are done with a computer of Intel Pentium 4 processor at 1500 MHz speed and 256 MB memory.

Stem-ends or calyx regions falsely recognized as defect can lead to errors in sorting of the fruit. Artificial neural network used to classify the fruit skin in this work, is not fully accurate especially in the recognition of stem-ends and calyxes. In order to eliminate such errors, we propose an additional step to further refine the results of ANN. It works as follows:

1. Regions recognized as stem-end/calyx by ANN are selected.
2. Average and range of intensities of these regions are calculated.
3. Then they are fed to a support vector machine (SVM), which is trained to make a binary classification (stem-end/calyx or not).
4. If SVM finds several stem-end/calyx regions, then the one with the highest score is selected.
5. Regions not regarded as stem-end/calyx by SVM are re-classified as defected. (Observations show that these regions are mostly coming from defected skin.)



object	class	score
1	0	-17.0
2	0	-0.3
3	1	1.5
4	1	1.9
5	1	5.3

Figure 7: Example of refinement process performed by using support vector machine. From left to right: original (top) and reference images (bottom), segmentation result of ANN and result of refinement.

An example of such a refinement can be observed in Figure 7. The synthetic '*refined*' image visually proves efficiency of this method, where several stem-end/calyx regions found by the ANN are further analyzed by SVM and the correct one is selected, while others are re-classified as defected skin.

CONCLUSIONS AND FUTURE WORKS

Several results of an artificial neural network based automatic defect segmentation system are introduced in this paper. A new attribute is introduced to eliminate false segmentations related to illumination artifacts and error rates of the system are found to be significantly better with this attribute, especially with the '*linear*' approach. Tests with several rejection rates of ANN are done and it is observed that rejection rate decreases false classifications of ANN proportionally. Effect of thresholds of post-processing step on segmentation performance of the system is also tested. Computation time of ANN to inspect one view of a fruit is found to be 450 ms, which is quite high compared to our objectives. But, if the images are downsampled to 128x128 pixels size, then computation time decreases to 40 ms, which is still high but encouraging. Therefore, effect of downsampling on segmentation accuracy should be examined.

The proposed sorting system segments defected areas by ANN and then either accepts of rejects the fruit by the area of its defect. A more realistic sorting system for apples, however, should also take into account the types of defects fruit contains. So, our next step will be to classify the segmented defects by their type and have a more realistic evaluation of our system. Effects of rejection rate and post-processing threshold will also be tested with this new evaluation.

As segmentation results of ANN are not fully accurate, a refinement step is also introduced to improve segmentation results. This refinement step is based on support vector machine that decides whether a stem-end/calyx region found by ANN is correct or not. Efficiency of this step is shown by a visual example in this paper, whereas its efficiency over the database is a future work.

ACKNOWLEDGEMENTS

We thank especially O. Kleynen and Prof. M.-F.Destain from the Mechanics and Construction Department of Gembloux Agricultural University of Belgium for providing us the database.

This project is funded by the Ministère de la Région wallonne of Belgium with Convention No: 9813783.

REFERENCE

[1] Anonymous. (2001). Common marketing standard for apples and pears. Commission Regulation (EC) No 1619 / 2001.

[2] Kleynen O., Leemans V. and Destain M.-F. (2003). Selection of the most efficient wavelenth bands for ‘Jonagold’ apple sorting. In: *Postharvest Biology and Technology*, 30, pp. 221-232.

[3] Leemans V., Magein H. and Destain M.-F. (1998). Defects segmentation on ‘Golden Delicious’ apples by using colour machine vision. In: *Comp. Elec. In Agriculture*, 20, pp. 117-130.

[4] Leemans V., Magein H. and Destain M.-F. (1999). Defect segmentation on ‘Jonagold’ apples using colour vision and a Bayesian classification method. In: *Comp. Elec. In Agriculture*, 23, pp. 43-53.

[5] Leemans V. and Destain M.-F. (2004). A real-time grading method of apples based on features extracted from defects. In: *Journal of Food Engineering*, 61, pp. 83-89.

[6] Li Q., Wang M. and Gu W. (2002). Computer vision based system for apple surface defect detection. In: *Comp. Elec. In Agriculture*, 36, pp. 215-223.

[7] Nakano K. (1997). Application of neural networks to the color grading of apples. In: *Comp. Elec. In Agriculture*, 18, pp. 105-116.

[8] Rennick G., Attikiouzel Y. and Zaknich A. (1999). Machine grading and blemish detection in apples. In: *Proc. Int. Sym. Signal Proc. App.*, pp. 567-570, Brisbane, Australia,.

[9] Unay D. and Gosselin B. (2004). A quality grading approach for ‘Jonagold’ apples. In: *Proc. IEEE Benelux Signal Proc. Sym.*, pp. 93-96, Hilvarenbeek, Netherlands.

[10] Wen Z. and Tao Y. (1999). Building a rule-based machine-vision system for defect inspection on apple sorting and packing lines. In: *Expert Systems with Applications*, 16, pp. 307-313.

[11] Yang Q. (1995). Automatic detection of patch-like defects on apples. In: *Proc. IEEE Image Proc. App. Conf.*, pp. 529-533.