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COMPARISON OF SELECTED CLASSIFICATION METHODS IN AUTOMATED OAK SEED SORTING

Summary

In this paper the results of automated, vision based classification of oak seeds viability i.e. their ability to germinate are presented. In the first stage, using a photo of the seed cross-section, a set of feature vectors were determined. Then three classification methods were examined: k-nearest neighbours (k-NNs), artificial neural networks (ANNs) and support vector machines (SVMs). Finally, a 73.1% precision was obtained for kNN and a 64 bin histogram, 78.5% for ANN and a 4 bin histogram and 78.8% for SVM with a 64 bin histogram.
Key words*: acorn classification, automated acorn sorting, image processing and analysis, kNN, ANN, SVM*

PORÓWNANIE WYBRANYCH METOD KLASYFIKACJI W AUTOMATYCZNYM SORTOWANIU NASION DĘBU

Streszczenie

W artykule zaprezentowano wyniki badań automatycznej, wizyjnej klasyfikacji nasion dębu pod względem ich żywotności, tj. zdolności do kiełkowania. W pierwszym etapie prac, na podstawie zdjęcia przekroju nasiona, wyznaczono zbiór cech, który w sposób niezależny od kształtu i rozmiaru poszczególnych obiektów pozwala na opisanie ich budowy anatomicznej. Następnie zbadano, dla wyselekcjonowanych wektorów cech, trzy metody klasyfikacji: k-najbliższych sąsiadów (k-NN), artificial neural networks (ANN) oraz maszynę wektorów nośnych (SVM). Uzyskano 73,1% precyzji rozpoznawania dla histogramu o długości 64 metodą kNN, 78,5% dla histogramu o długości 4 dla ANN i 78,8% dla histogramu o długości 64 metodą SVM.
Słowa kluczowe*: klasyfikacja żołędzi, automatyczne sortowanie żołędzi, przetwarzanie i analiza obrazów, kNN, ANN, SVM*

1. Introduction

The preparation of cuttings with high germination ability is a very important issue in oak growing. Traditionally, this process involves seed scarification (cutting the top part of the acorn) and visual evaluation by a trained expert [5]. Due to the large number of oak seeds, which require this kind of analysis and limited time to accomplish this task, significant human resources have to be involved. This turns out to be very expensive and inconvenient.

An automaton able to perform the scarification followed by visual evaluation of the cross-section and finally seed sorting could be a solution to the problem outlined above. In this paper the research results on automated, vision based seeds cross-section analysis are presented. The proposed solution is a classic example of a vision system, which consists of the following steps: image preprocessing, feature extraction (analysis) and classification. In should be emphasized that each of the mentioned steps is very important for the final system performance. In particular, two key elements are feature vector extraction, which should describe the seeds' "quality" (usually the stage of mummification changes) and the classification. During the study several different options for feature vector construction and three classifiers: k-nearest neighbours (kNNs), artificial neural networks (ANNs) and support vector machines (SVMs) were examined. In similar works for wheat seeds classification neural networks were used [2, 7, 8].

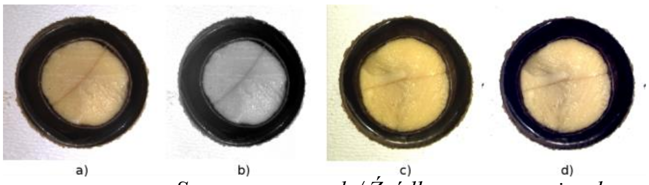
The performance of particular classification methods was evaluated for greyscale image histogram and HSV (Hue, Saturation, Value) colour features of the seeds' cross-sections.

2. Feature vector computation

The proposed feature vector computation process consisted of the following stages: image acquisition, image normalization and feature extraction. In the experiments a set of 400 images of oak acorns cross-sections was used.

The preliminary analysis has shown a large lighting variance across the image dataset. These differences included both uneven lighting within a single image and variable lighting between different images. Therefore, it was necessary to develop methods to compensate for the disparities.

Two solutions were proposed – one for non-uniformity of luminance compensation and second for colour normalization. Both approaches were based on a similar mechanism and made use of the presence of uniform white background in the image. For the first approach – based on the lower and upper parts of the image (without the acorn), a brightness function was determined, applied as to unify lighting in the entire image. An example of this procedure is presented in Figure 1a and 1b. As for the second case, the colour components C_b and C_r (after initial image conversion from RGB to YC_bC_r) in nominally white areas (C_b and C_r values should be 128) were determined. Then, using the computed difference between the expected and actual value, a correction for all of the pixel values was applied. A sample result for combined brightness and colour compensation is presented in Figure 1c and 1d.

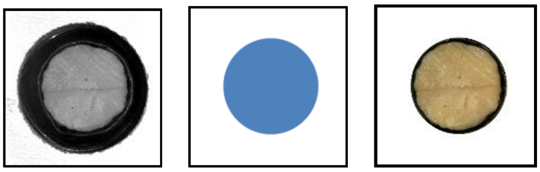


Source: own work / Źródło: opracowanie własne

Fig. 1. Image normalization example. Input image (a), image after brightness normalization (b), input image (c), image after brightness and colour normalization (d)

Rys. 1. Przykład normalizacji. Obraz wejściowy (a), obraz po normalizacji jasności (b), obraz wejściowy (c), obraz po normalizacji jasności i koloru (d)

During preliminary analysis a number of different features of acorns cross-section were considered. They were mainly based on brightness and colour, as these two properties were mentioned by experts (they used them in the manual visual evaluation of seeds). All the described below operations were performed for the area covering only the cross-section i.e. cotyledons and shell. Therefore, a manually determined mask, which defined the region of interest (ROI) was used. An example of the mask and its application is shown in Figure 2.



a) b) c)

Source: own work / Źródło: opracowanie własne

Fig. 2. Determining the region of interest. Input image (a), manually-chosen mask (b), the selected ROI (c)

Rys. 2. Maskowanie obszaru analizy. Obraz wejściowy (a), maska wyznaczona ręcznie (b), obszar analizy (c)

Among the considered features were mean, median and variance of greyscale and colour images, as well as histograms and cumulative histograms for greyscale images. These values can be calculated for both the whole ROI area, as well as for its different parts (for example rings). Therefore, the number of features used in the classification stage can be increased.

After some initial result analysis, it was decided to carry out more extensive experiments with greyscale histograms (number of used bins: 4, 8, 16, 32, 64), as well as mean and median for brightness and colour (in HSV colour space) images.

In the study of acorns viability classification a set of 400 images presented oak seeds after scarification. This set was divided into two parts. One for classifier training and second for quality evaluation (i.e. train and test sets). Both of them contained varying images (“obvious” and “difficult” cases). There were 240 samples in the training set and 160 in the test set. For both groups the “ground truth” i.e. the information if a given seed germinated was available.

3. The used classifiers

3.1. K-nearest neighbours

The concept of k nearest neighbours (kNN) is based on finding k feature vectors in the training set, which are most in terms of a certain measure to the currently considered sample (e.g. from the test set or input device) [3 and 6]. If each component of a sample in the training set is considered as another dimension in a certain space and the particular values are coordinates in that dimension, the similarity of two samples (described by these coordinates) is defined by a metric.

The selection of parameters i.e. appropriate number of neighbours and a distance measure has an impact on the classification performance. The k value should allow to minimize the probability of misclassification of the considered sample by taking into consideration only the sufficiently close neighbours. During the experiments, the following k values were used: 1, 3, 5, 7, 9 and 11. It was assumed that the distance between two samples was computed with the Euclidean metric. All experiments were performed in Matlab software.

3.2. Artificial neural networks

Artificial neural networks, which model the behaviour of neural networks present in neural system of animals and humans (at different levels of specificity), are a well-known and proved classifier [4 and 10]. The processing elements (i.e. neurons) are arranged in connected layers. Parameters of each connection (so-called weights) are determined via a learning process using a set of examples. These set is divided into a training, validation and test part. The first two are used in the network training (directly and supportive) and the third is used to evaluate the classifiers performance only. In the experiments the Statistica® Statsoft software was used. If two classes were considered i.e. “grown” and “not grown” the output layer of the network contained only one neuron. To the first class the value “0” and to the other “1” was assigned. In case of using a single neuron with a continuous function is was necessary to use a threshold. The value 0.5 was used to separate elements of class “0” from class “1”.

3.3. Support Vector Machines (SVM)

Support Vector machine are binary linear classifiers [1 and 9]. They allow to separate two classes by a hyper plane. Their parameters (support vectors) are determined in a supervised learning procedure. Among the many possibilities, the one that can best separate the two classes (according to a particular cost function) is selected. Then, the classification of a particular sample involves the determination of its location with correspondence to the hyper plane. For non-linear problems the so-called kernel trick is used. It allows increasing the dimensionality of the feature vector and usually improving the performance. In the experiments the SVM implementation available in Matlab software was used.

4. The obtained results

The goal of the described research was the determination of a feature vector (Section 2) and classification method (Section 3) which will have the best performance in visual based oak seeds evaluation. In case of a binary classification there are four possible outcomes TP (true positive – should grow and did grow), TN (true negative - shouldn't grow and didn't grow), FP (false positive – should grow, but didn't grow), FN (false negative – shouldn't grow and did grow). On their basis the following measures can be determined: sensitivity (TP / (TP + FN)); specificity (TN / (TN + FP)); precision (TP / (TP + FP)); accuracy ((TP + TN) / (TP + FP + FN + TN)). All these values can be expressed as percentages. It was decided that for the automaton the most important parameter is precision, as the main observed problem was the distinction between TP and FP.

4.1. Greyscale histogram based classification

The obtained results for pre-selected histogram based features and kNN, ANN and SVM classifiers are summarized in Table 1. For the ANNs the best results were achieved for 4 bins histogram. The corresponding network had 4 neurons in the input layer, 4 in the hidden one and one as the output. The results can be explained by the size of the used training set. For larger histograms and therefore larger networks the set was too small to allow effective learning (weight determination). For the kNN method with k=7 the best precision was obtained for a 64 bin histogram, whereas for SVM with RBF (Radial Basis Function) kernel the best performance was observed for 64 bin histogram.

Table 1. Classification performance for histogram based features

Tab. 1. Miary jakości klasyfikacji na podstawie wartości histogramów

METHOD	**ANN**	**kNN**	**SVM**
NUMBER OF HISTOGRAM BINS	**4**	**64**	**64**
SENSITIVITY [%]	81.0	90,5	76.2
SPECIFICITY [%]	85.6	78.4	86.6
PRECISION [%]	**78.5**	**73.1**	**78.7**
ACCURACY [%]	83.8	83.1	82.5

Source: own work / Źródło: opracowanie własne

4.2. HSV colour space based classification

The obtained results for selected HSV colour space based features and classifiers : kNN, ANN and SVM are summarized in Table 2. In the experiments mean and median values separately for HSV colour components, six values (mean and median for H+S+V), as well as additional mean and median for GR (green) and GRN (normalized green component) were analysed.

Table 2. Classification performance for HSV colour space based features

Tab. 2. Miary jakości klasyfikacji na podstawie reprezentacji barwnej HSV

FEATURE	V	10 param*	10 param.*
METHOD	**kNN**	**ANN**	**SVM**
SENSITIVITY [%]	65.1	68.3	44.4
SPECIFICITY [%]	74.2	78.4	89.7
PRECISION [%]	**62.1**	**67.2**	**73.7**
ACCURACY [%]	70.6	74.4	71.9

*(GR+GRN+H+S+V, median and average)

Source: own work / Źródło: opracowanie własne

The precision results for kNN method were in the range [50.5%, 62.1%]. The best performance was obtained for a single feature - median of the V component and k=5. Both the ANN and SVM method achieved the best results for 10 features. In the first case they were in range [50.5%, 67.2%] and in the second [50.0%, 73.7%].

5. Summary

A comparison of the three analysed classification methods is presented in Table 3. The used features and classifiers parameters were selected using the best precision value.

Table 3. Best feature vectors and classification performance for each of the considered classifiers

Tab. 3. Najlepszy zestaw cech dla każdej z metod i wyniki klasyfikacji według tego zestawu

FEATURE	Histogram 64 BIN	Histogram 4 BIN	Histogram 64 BIN
METHOD	**kNN**	**ANN**	**SVM**
SENSITIVITY [%]	90.5	81.0	76.2
SPECIFICITY [%]	78.4	85.6	86.6
PRECISION [%]	**73.1**	**78.5**	**78.7**
ACCURACY [%]	83.1	83.8	82.5

Source: own work / Źródło: opracowanie własne

In case of HSV colour space based features, the best results were obtained by the SVM method. However, a similar performance was achieved for ANN and 4 bin histograms. The kNN performance was about 5% percentage points lower (for 64 bin histogram). It can be concluded that ANN and SVM allow for the considered problem to achieve comparable results, with a slight advantage of the second approach.

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