Computers and Electronics in Agriculture 122 (2016) 185–190

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Wheat grain classification by using dense SIFT features with SVM classifier

Murat Olgun [a,1], Ahmet Okan Onarcan [b,2], Kemal Özkan [b,2], Şahin Işik [b,2], Okan Sezer [c], Kurtuluş Özgişi [c], Nazife Gözde Ayter [a,1], Zekiye Budak Başçiftçi [a,1], Murat Ardiç [c], Onur Koyuncu [c,*]

[a] Eskişehir Osmangazi University, Faculty of Agriculture, Department of Field Crops, Eskişehir, Turkey
[b] Eskişehir Osmangazi University, Faculty of Engineering and Architecture, Department of Computer Enginering, Eskişehir, Turkey
[c] Eskişehir Osmangazi University, Faculty of Science and Letters, Department of Biology, 26480 Eskişehir, Turkey

ARTICLE INFO

Article history:
Received 19 February 2015
Received in revised form 23 December 2015
Accepted 29 January 2016

Keywords:
Wheat identification
Grain classification
Dense SIFT features
k-means clustering
Support Vector Machines
Bag of Word Model

ABSTRACT

The demand for identification of cereal products with computer vision based applications has grown significantly over the last decade due to economic developments and reducing the labor force. With this regard, we have proposed an automated system that is capable to classify the wheat grains with the high accuracy rate. For this purpose, the performance of Dense Scale Invariant Features (DSIFT) is evaluated by concentrating on Support Vector Machine (SVM) classifier. First of all, the concept of *k*-means clustering is operated on DSIFT features and then images are represented with histograms of features by constituting the Bag of Words (BoW) of the visual words. By conducting an experimental study on a special dataset, we can make a commitment that the proposed method provides the satisfactory results by achieving an overall 88.33% accuracy rate.

1. Introduction

Wheat (*Triticum* spp.) is a major food source in the world and it is commonly grown in most of the countries. It has wide adaptability to various environments including irrigated and dry land conditions; this explains that why it prevails in food production of the world. Healthy wheat production mainly requires certified pure grain use and in production process grains shouldn't be mixed with different genotypes. The identification of varieties requires some knowledge of the appearance of grains and is assisted by information regarding its grain appearance. Confusion in grain appearance is a frequently encountered problem, especially in Turkey, where the number of wheat genotypes is very large. Commercially, wheat can be categorized with two groups as grain hardness (soft, medium-hard and hard) and appearance (color, degree of damage by insects or fungi, shriveling, shape of embryo). This separation can be branch out by considering growing habit (spring or winter). Also each subclasses can be ordered by their grades depending upon the price of a wheat stock as applying premiums or penalties by taking such properties (rain, heat, frost, insect and mould damage) and the cleanliness (dockage and foreign material) of the wheat lot into account. Grading factors can also be varied with respect to quality of grain such as protein content and sedimentation test weight in wheat trading as emphasized in Peña (2002).

Classification of wheat grains can be made in two ways as manually or automatically. In manual way, the type and the quality of wheat grain is specified based on an expert judgement. However, the judgement of the expert is inaccurate for some cases when the difference between the variety and the quality of wheat species is very close to each other. Thereby, the decision of the expert could result in financial loss, bankrupt or loss of confidence on behalf of manufacturer. In another way, using image processing and pattern recognition algorithms, called expert systems, with a purpose for wheat classification are slightly more accurate than manual way. In this way, the shape, the texture, the length and the color features are considered and combined to construct the feature vector, which represents the image with reduced dimension by discriminative characteristics. Later, the obtained feature set is put forward as input into a machine learning algorithm, i.e., K-Nearest Neighbor (K-NN), Decision Tree (DT) or Artificial Neural Network (ANN), to obtain a concise decision about its label. It should be noted that using expert systems depending upon the pattern recognition methodologies is more effective, fairer, cheaper and faster when compared with expert judgement.

* Corresponding author.
E-mail address: omurkoyuncu@gmail.com (O. Koyuncu).
[1] Tel.: +90 222 3242991/4862.
[2] Tel.: +90 222 2393750/3275.

http://dx.doi.org/10.1016/j.compag.2016.01.033
0168-1699/

Going through the previous studies on wheat classification, we found a few studies as counted something on the fingers of two hands. In Zayas et al. (1989) developed a structural prototype for discrimination of wheat and non-wheat components in a grain sample, by using a multivariate discriminant analysis technique. In referred paper, the execution time for discrimination between wheat and non-wheat was elapsed as about 10 s. Also, priorly, the same authors carried out another two experiments as discrimination between Arthur and Arkan wheats (Zayas et al., 1985) and discrimination between wheat classes (hard red winter, soft red winter and hard red spring) and varieties by benefiting from image processing methods (Zayas et al., 1986) with maximum 99.52 (1 out of 209 grain was not identified correctly) and 83% accuracy rates in the test stage, respectively. In another work, Majumdar and Jayas had reported four different approaches for classification commercial cereal grains by employing morphology models (Majumdar and Jayas, 2000a), color models (Majumdar and Jayas, 2000b), texture models (Majumdar and Jayas, 2000c) and hybrid one as combination of morphology, color and texture models (Majumdar and Jayas, 2000d). Moreover, the discrimination of wheat class and variety by digital image analysis of whole grain samples (Neuman et al., 1987), the performance of pattern recognition methods for the separation of cereal grains (corn, soybeans, rice, sorghum grain, barley and wheat) (Lai et al., 1986), the identification of Australian wheat varieties (Myers and Edsall, 1989), identification of Canada Western Red Spring (CWRS) wheat (Sapirstein and Kohler, 1999) and analyzing the shape Indian wheat varieties (Shouche et al., 2001) by image analyses techniques, particularly with morphological operations (Zapotoczny et al., 2008) had been presented and realized by concentrating on some computer programs.

Recently, a crowded set of machine learning techniques have been experimented to determine some wheat types. In a work (Guevara-Hernandez and Gomez-Gil, 2011), a machine vision system was developed for classification of wheat and barley grains based on the 21 morphological features, 6 of them were color features, 72 of them were texture features, totally 99 features. To reduce high dimension of feature set and eliminate the ones which gain the less contribution, the sequential forward feature selection has utilized after zero mean normalization, weighting and sorting processes with respect to larger Fisher discriminant ratio. The experimented approach achieves an accuracy rate that is higher than 99% when conducting on two classes. In another work (Ronge and Sardeshmukh, 2014), the widely known four Indian wheat seed varieties (Lokvan Gujrat, Lokvan MP, MP sure, Khapali) are classified by extracting 131 textural features as 32 gray level textural features, 31 Local Binary Pattern (LBP) features, 31 Local Similarity Patterns (LSP) features, 15 Local Similarity Number (LSN) features, 10 Gray Level Co-occurrence matrix (GLCM) features and 12 Gray Level Run-length Matrix (GLRM) features. By observing the results, the average accuracy values are 66.68% and 39% in case of intra class classification with ANN and K-NN classifiers, respectively. Again, the Multi-Layer Perceptron (MLP) Neural Network based classification system (Pazoki and Pazoki, 2013) has been developed to distinguish the six classes of rain fed wheat grain cultivars with 21 statistical features. The average accuracies returned from the system have been reported as 86.48% and 87.22% as before and after applying the utility additive (UTA) algorithm to ignore the less promised features. Moreover, six varieties (Demir, Gün, İkizce, Mızrak, Seval, Tosunbey) of bread wheat are classified by using the common vector approach (CVA), which is a subspace based feature extraction method (Gulmezoglu and Gulmezoglu, 2015). By using the CVA, firstly, a common vector which represents common or invariant properties of each class is computed and then a given test image is assigned to its label based on minimum distance criteria. The average accuracy for 500 test images has been reported as 36.7. Also, the impact of four machine learning algorithms (One-R, J48, IBK and Apriori) (Romero et al., 2013) for the prediction of wheat yield from several phenotypic plant traits has been examined by using the machine learning software WEKA (Hall Mark, 2003). Authors emphasized that among the aforementioned algorithms, the best overall accuracy obtained from Apriori, which is noted as 90% when executed to predict drum wheats for three cities. In given study, the measured yield components have considered as features in case of prediction.

Despite the good performance of proposed methods, the limitations of them become apparent when considering big datasets with high sample size and dimension, which are not carried out in related works. In another word, training a pattern recognition system with the low number of samples does not give stable and precise results in terms of accuracy and effectiveness in reality. We consider this detail and present a solution to close the gap with a different wheat classification approach. With this aim, we have proposed an algorithm based on the dense SIFT features, which is a popular feature extraction method utilized in tasks of object recognition (Loncomilla and Ruiz-del-Solar, 2005), object tracking (Zhou et al., 2009) and image retrieval (Ledwich and Williams, 2004). The reason for choosing DSIFT instead of SIFT, is attributed to its good results by obtaining descriptors from every locations, when compared with performance generated from specific locations as performed in SIFT algorithm. Moreover, the study on comparison of feature detectors and descriptors for object class matching (Hietanen et al., 2015) emphasizes that the performance DSIFT is superior to some feature selection methods. Also, SVM is selected as an optimized classifier that generates an optimal decision boundary between classes. The obtained features are concentrated on SVM classifier. The experimental results show that the proposed method gives satisfactory, realistic and convincing accuracy rates when making trials on 40 classes as consists of 160 samples per each class.

The rest of paper is organized as follows. Section 2 introduces the materials and procedure for wheat classification. The related work is presented in Section 3. In Section 4, the performance of proposed method on special dataset is discussed with objective evaluation measures. Finally, a conclusion is touched and future work is discussed.

2. Material and methods

The classification procedure of wheat objects is conducted on most of the state of art feature extraction methods. The related work is summarized with Fig. 1. By inspecting Fig. 1, some stages that are required for a particular classification problem are considered as dense SIFT features that are extracted in (i), (ii) the *k*-means clustering is operated on DSIFT features, (iii) the BoW model from the histogram clustering features are acquired and finally SVM classifier is utilized on BoW model in order to identify wheat objects.

2.1. Dense scale invariant feature transform

Scale-invariant feature transform (or SIFT) (Lowe, 1999, 2004) is a computer vision algorithm to represent and identify objects with some local and distinctive features, proposed by David Lowe in 1999. The main objective of SIFT algorithm obtains the descriptors that are invariant to rotation, scale, variation in illumination and robust to geometric transformations which are isometry, similarity, affine, projective and inversion transformations.

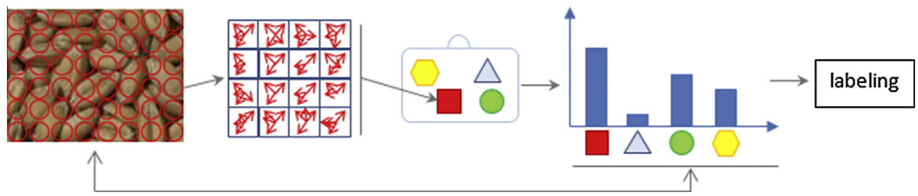

Fig. 1. Image representation by BoW models and labeling.

Briefly, the stages involved in SIFT can be summarized as scale space construction, scale-space extreme detection, key point localization, edge response elimination and orientation assignment. In stage of scale space construction, local scale-space maxima of the Difference of Gaussian (DoG), called potential key points, are computed through different DoG scales. In this stage, some extreme with absolute value smaller than a predefined threshold are eliminated. Next, the orientation is assigned to each key points and weighting processes is carried out based on the computed gradient. To eliminate the edge response, SIFT uses the eigenvalues of a 2×2 Hessian Matrix for each key point stated on different scales in order to check whether the processed point is edge or not. Each Hessian matrix is computed on different scales (x, y, σ), where x and y refer to pixel coordinates and σ indicates Gaussian smoothing sigma value. Then, the smaller (α) and largest (b) eigenvalues are calculated from a processed Hessian matrix. The ratio obtained from eigenvalues (α, β) is expected to be minimum in order to satisfy the edge condition as $((\alpha+\beta)^2/(\alpha\beta)) < ((r+1)^2/r)$, where $r = (\alpha/\beta)$. In last stage, SIFT generates a feature vector by considering the direction of a key point, where the gradient strength is maximal. By centering the key point, a 16×16 grid is determined and divided into the 4×4 sub-regions. To compute the descriptors, called orientation of key points, the window with 8 bins (8×8) is rotated relative to the key point orientation. Since the dimension of specified region is 16 and each rotated windows are 8 bins, the vector has 128 elements. Hence, the compact, more distinctive and robust descriptors are obtained against to variation in illumination and camera viewpoint.

In presented work, we have focused on the Dense SIFT (DSIFT) algorithm, which is derived from the SIFT algorithm. The main trait of DSIFT over the SIFT algorithm utilizes a sampling procedure to reduce the time cost in SIFT algorithm. An overview presentation for DSIFT based feature extraction strategy is demonstrated in Fig. 2.

By considering Fig. 1, a wheat image is handled with grid representation, by dividing into square regions. As we can see that the image is divided into the windows with equal size as given in Fig. 2(a). Later, SIFT descriptors are extracted on specified regions, by representation with Fig. 2(b) and the descriptors that are invariant to rotation, translation and illumination changes, are selected to represent a wheat object, Fig. 2(c). Once the descriptors are obtained, they are put into the k-means clustering to build a model of clustered features.

2.2. k-means clustering features

Prior to the BoW model construction, the dimension of features which are obtained with DSIFT algorithm, should be reduced in terms of speed and accuracy. With this aim, the k-means clustering is carried out on obtained features. Specifically, k-means clustering algorithm (Jain, 2010; Kanungo et al., 2002) is a popular and unsupervised learning algorithm as the label of groups is unknown. In clustering procedure, the aim is to treat the k mutually exclusive clusters from n observations by an iterative classification methodology. In this way, firstly the k means are called as centers and are determined with a heuristic or deterministic way, then each samples are assigned into a unique cluster with respect to the minimum distance measure. At the end, the huge size data is represented with k clusters.

2.3. Bag of words model

The main idea behind the using Bag of Words Models (BoW) represents the images with visual words. In this model a patch, shape descriptor or region, which exhibits the spatial characteristic of object, is considered as the visual words. Previously, the BoW model is carried out in image retrieval (Philbin et al., 2007), object (Nowak et al., 2006) and text classification (Joachims, 1997), text representation for sentence selection (Caropreso and Matwin, 2006) and topic modeling tasks (Wallach, 2006). Concordantly, we have adapted the BoW model with a purpose for wheat object representation and identification. With a BoW model, it is possible to represent the objects with less size of features by computing the histogram of visual words.

2.4. Support Vector Machines

The objective of SVM classifier (Cevikalp et al., 2011; Özkan et al., 2015; Ruiz-Pinales et al., 2006), which is also known as a hyper plane classifier, is to determine an optimal line to separate the training set of the given two classes. To this end, a model is constructed to assign the test samples into one of classes. Let suppose that our aim is to assign a given training set, $D = \{(\mathbf{x_1}, L_1), (\mathbf{x_2}, L_2), \ldots, (\mathbf{x_M}, L_M)\}$, into the two groups with SVM concept. In given set, $\mathbf{x}_i$ refers to a vector and L_i denotes the label of vector to be assigned as either positive (+1) or negative (−1). Then any unknown vector $(\mathbf{x_{test}})$ can assigned with respect to following criteria;

$$f(\mathbf{x_{test}}) = \sum_{i=1}^{M} \{\alpha_i L_i (\mathbf{x_i^T x_{test}}) + b\} \qquad (1)$$

where α_i $(i = 1, 2, \ldots, M)$ are the nonzero coefficients as obtained with the quadratic programming, $(|b|/\|\mathbf{w}\|)$ is the perpendicular distance from the optimal hyper plane to the origin and $\mathbf{w}$ is the normal vector of the hyper plane. In linear separable case, the sign of f function estimates the label of test vector. For multi-class case, the concept of SVM for two class separation is operated as one-against to all.

3. Proposed method

In this study, it is aimed at developing a classification model by evaluating the performance of DSIFT features. Typically, a classification algorithm consists of three steps as feature extraction, training (model construction) and test stages. Similarly, the proposed algorithm mainly involves three stages, which are obtaining the BoW model with visual words, a decision model construction with SVM and specifying a test process.

By analyzing Fig. 3, the taken images are put forward to the DSIFT feature extraction stage. The obtained DSIFT feature vector

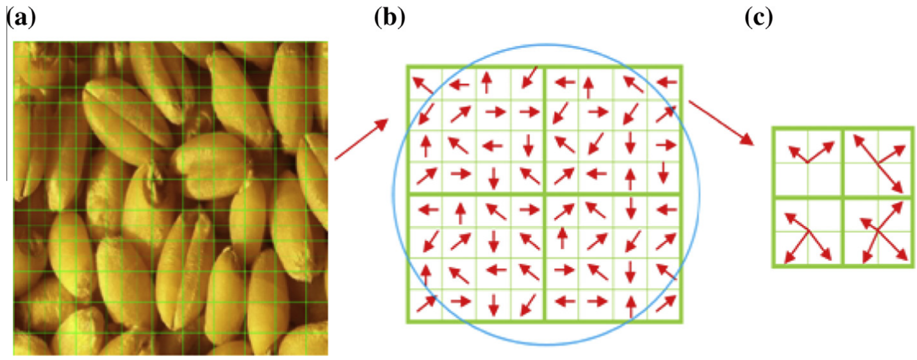

Fig. 2. The process of generating the DSIFT features.

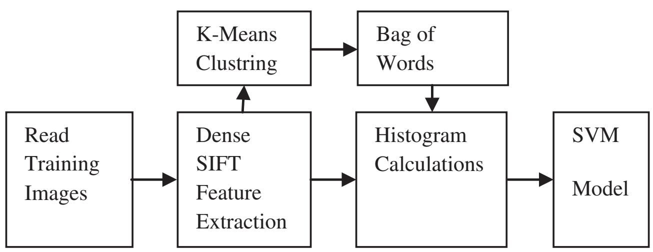

Fig. 3. Creating bag of words and obtaining the SVM model in training stages.

size is 600 × 128 per each sample. Then, the dimensions of features are reduced as obtaining k clusters by accompanied k-means clustering algorithm. The value of k is determined as 1000. Finally, a BoW model that includes the discriminative visual words is constructed for training stage. During training phase as shown in Fig. 3, the system is trained by concentrating the DSIFT features onto the SVM classifier. Once the BoW model is constructed, the spatial histograms of visual words are computed (Lazebnik et al., 2006). The reason to use histogram of visual words can be expressed as reducing the dimension of features and improving the contribution of them according to the occurred counts. The returned Histogram based on features encapsulates the local characteristic of visual words within a wheat object. For the sake of high accuracy, the grain of SVM is specified with x^2 (Vedaldi and Fulkerson, 2010; Vedaldi and Zisserman, 2012) and the optimization parameter of SVM is determined as 10 which is used to scale the loss function instead of the regularization.

The next stage of proposed algorithm defines the states of assigning an unknown wheat object into the related class. As shown in Fig. 4, the same operations that are executed in training phase, is utilized as firstly the DSIFT features are extracted from the input image, the image is represented with its histograms features, and finally the class label of processed image is estimated depending upon the decision returned from the SVM classifier. Hence, all objects are classified and performance of system is determined with respect to miss classified objects.

4. Experiments and results

4.1. Dataset

To validate the distinctiveness property of the proposed method, a variety of experiments are conducted on a special dataset that includes the wheat images of our country. The referred dataset involves 40 wheat grain species (classes) (Adana 99, Ahmetağa, Aldane, Alparslan, Altınbaşak, Ayyıldız, Bayraktar, Bereket, Canik, Ceyhan, Çetinel, Çukurova 86, Demir, Doğankent, Ekiz, Eser, Fuatbey, Gökhan, Göksu, Gün, İkizce, Karatoprak, Kenanbey, Kınacı, Kirik, Lütfübey, Osmaniyem, Özcan, Palandöken, Pandas, Sakin, Sarıbaşak, Seri 82, Seval, Seyhan, SHAM, Uzunyayla, Van Çeşidi, Yüreğir 89, Zencirci). The some visual samples of utilized dataset are given in Fig. 5, where each label indicates a different wheat type.

4.2. Objective results

To verify the performance of proposed method, an extensive experimental study using a smart decision system with SVM and histogram features is conducted on given dataset. The given images include real world abruptions including, zoom and scale change, rotation, and moisture and illumination variation. Moreover, a small inter-class variability occurs for each category and there is no background clutter. There are 40 wheat grains with 160 samples as totally 6400 images. All images are in the form of 726 × 544 pixels. In this work, 10-fold cross validation technique was used to objectively evaluate the entire wheat grains dataset. In case of performance evaluation, a confusion matrix was constructed by using 144 images for training the system and randomly chosen 16 images for testing purpose each fold. Since the utilized dataset consisted of 40 classes, we have executed the algorithm for 5760 images in training stage and 640 images in test stage each fold.

Table 1 shows the results generated from the proposed algorithm as visualized with a confusion matrix. Due to the page limitation to visualize the 40 × 40 confusion matrix, we only give the diagonal elements of confusion matrix, which refers to the number of correctly classified labels. Specifically, each row indicates original class whereas each column indicates the predicted class. Upon inspecting the results given in Table 1, the proposed method gives satisfactory outcomes with overall 88.33% accuracy rate.

By expanding the evaluation, the G2, G4, G6, G9, G17, G20 and G29 species are classified with 100% accuracy rate. Also, we can see that the G10, G12, G30, G32 and G38 species are intermixed with other wheat species due to similarity in illumination variation. Although the classification of wheat types is a challenging problem because of the high intra-species variability and low inter-species variation in datasets, the proposed method presents successful and admitted results.

5. Conclusion

In this paper, we have reported a new approach to identify the wheat grains by using a smart decision system. The implemented system promises to make the automated classification of wheat objects with an effortless way and without losing the time. Moreover, the experimental results obtained on special dataset; show

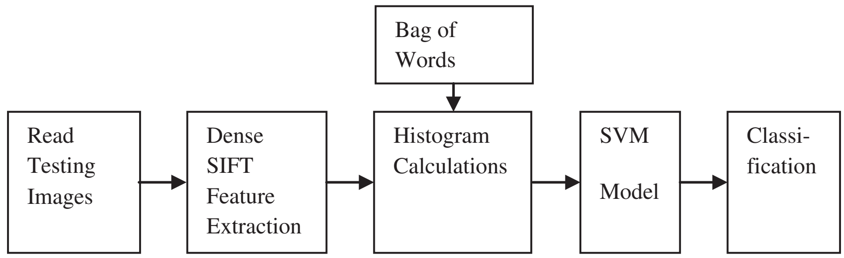

Fig. 4. Test stage.

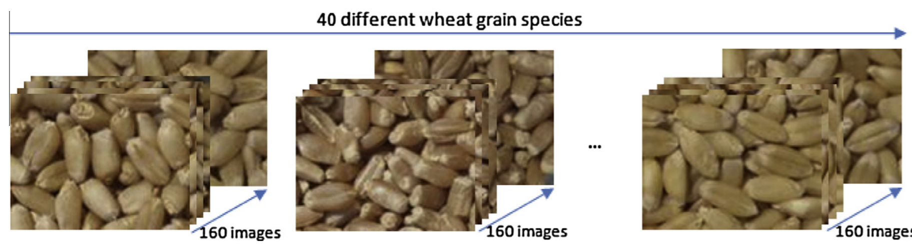

Fig. 5. Some visual samples of dataset.

Table 1
The results generated from the proposed algorithm as visualized with a confusion matrix.

Group number	Correct classification	Group number	Correct classification
G1	140/160	G21	151/160
G2	160/160	G22	145/160
G3	154/160	G23	144/160
G4	160/160	G24	153/160
G5	131/160	G25	129/160
G6	160/160	G26	152/160
G7	146/160	G27	143/160
G8	156/160	G28	133/160
G9	160/160	G29	160/160
G10	113/160	G30	97/160
G11	140/160	G31	147/160
G12	113/160	G32	114/160
G13	155/160	G33	146/160
G14	150/160	G34	157/160
G15	153/160	G35	109/160
G16	122/160	G36	128/160
G17	160/160	G37	158/160
G18	131/160	G38	117/160
G19	125/160	G39	158/160
G20	160/160	G40	123/160
# of correct classified images		5653	
# of total test images		6400 = (40 × 160)	
Accuracy		88.33%	

that the utilized features are discriminative and robust when the contribution is considered in term of accuracy rate. The misclassified samples could be attributed to lack of stability of selected features due to high level of similarity in interclasses. The obtained 88.33% accuracy rate clearly shows that the proposed method is robust and can be used in real time applications. Another contribution of this study on wheat classification identifies the wheat grains by a simple and cheap operation, without using complex systems and expensive equipment.

References

Caropreso, M.F., Matwin, S., 2006. Beyond the bag of words: a text representation for sentence selection. In: Lamontagne, L., Marchand, M. (Eds.), Advances in Artificial Intelligence. Springer, Berlin, Heidelberg, pp. 324–335. http://dx.doi.org/10.1007/11766247_28.

Cevikalp, H., Yavuz, H.S., Edizkan, R., Gunduz, H., Kandemir, C.M., 2011. Comparisons of features for automatic eye and mouth localization. In: 2011 International Symposium on Innovations in Intelligent Systems and Applications (INISTA). IEEE, pp. 576–580. http://dx.doi.org/10.1109/INISTA.2011.5946152.

Guevara-Hernandez, F., Gomez-Gil, J., 2011. A machine vision system for classification of wheat and barley grain kernels. Spanish J. Agric. Res. 9 (3), 672–680. http://dx.doi.org/10.5424/sjar%2F20110903-140-10.

Gulmezoglu, M.B., Gulmezoglu, N., 2015. Classification of bread wheat varieties and their yield characters with the common vector approach. In: International Conference on Chemical, Environmental and Biological Sciences (CEBS2015), Dubai, pp. 120–123. http://dx.doi.org/10.15242/IICBE.C0315090.

Hall Mark, E.F., 2003. The WEKA data mining software: an update. SIGKDD Explor. 11 (1).

Hietanen, A., Lankinen, J., Kämäräinen, J.K., Buch, A.G., Krüger, N., 2015. A comparison of feature detectors and descriptors for object class matching. Neurocomputing. http://dx.doi.org/10.1016/j.neucom.2015.08.106.

Jain, A.K., 2010. Data clustering: 50 years beyond K-means. Pattern Recogn. Lett. 31 (8), 651–666. http://dx.doi.org/10.1016/j.patrec.2009.09.011.

Joachims, T., 1997. A probabilistic analysis of the rocchio algorithm with TFIDF for text categorization. In: Fisher, D.H. (Ed.), Proceedings of the Fourteenth International Conference on Machine Learning. Morgan Kaufmann Publishers Inc., San Francisco, pp. 143–151.

Kanungo, T., Mount, D.M., Netanyahu, N.S., Piatko, C.D., Silverman, R., Wu, A.Y., 2002. An efficient k-means clustering algorithm: analysis and implementation. IEEE Trans. Pattern Anal. Mach. Intell. 24 (7), 881–892. http://dx.doi.org/10.1109/TPAMI.2002.1017616.

Lai, F., Zayas, I., Pomeranz, Y., 1986. Application of pattern recognition techniques in the analysis of cereal grains. Cereal Chem. 63 (2), 168–172.

Lazebnik, S., Schmid, C., Ponce, J., 2006. Beyond bags of features: spatial pyramid matching for recognizing natural scene categories. In: Fitzgibbon, A., Taylor, C.J., LeCun, Y. (Eds.), Computer Vision and Pattern Recognition 2. IEEE, pp. 2169–2178. http://dx.doi.org/10.1109/CVPR.2006.68.

Ledwich, L., Williams, S., 2004. Reduced SIFT features for image retrieval and indoor localisation. In: Proceedings of Australasian Conference on Robotics and Automation (ACRA).

Loncomilla, P., Ruiz-del-Solar, J., 2005. Improving SIFT-based object recognition for robot applications. In: Roli, F., Vitulano, S. (Eds.), Image Analysis and Processing–ICIAP 2005. Springer, Berlin, Heidelberg, pp. 1084–1092. http://dx.doi.org/10.1007/11553595_133.

Lowe, D.G., 1999. Object recognition from local scale-invariant features. In: Computer Vision, 1999. The Proceedings of the Seventh IEEE International Conference on 2. IEEE, pp. 1050–1057. http://dx.doi.org/10.1109/ICCV.1999.790410.

Lowe, D.G., 2004. Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vis. 60 (2), 91–110. http://dx.doi.org/10.1023/B:VISI.0000029664.99615.94.

Majumdar, S., Jayas, D., 2000a. Classification of cereal grains using machine vision: I. Morphology models. Trans. ASAE 43 (6), 1669–1675. http://dx.doi.org/10.13031/2013.3107.

Majumdar, S., Jayas, D., 2000b. Classification of cereal grains using machine vision: II. Color models. Trans. ASAE 43 (6), 1677–1680. http://dx.doi.org/10.13031/2013.3067.

Majumdar, S., Jayas, D., 2000c. Classification of cereal grains using machine vision: III. Texture models. Trans. ASAE 43 (6), 1681–1687. http://dx.doi.org/10.13031/2013.3068.

Majumdar, S., Jayas, D., 2000d. Classification of cereal grains using machine vision: IV. Combined morphology, color, and texture models. Trans. ASAE 43 (6), 1689–1694. http://dx.doi.org/10.13031/2013.3069.

Myers, D., Edsall, K., 1989. The application of image processing techniques to the identification of Australian wheat varieties. Plant Variet. Seeds 2, 109–116.

Neuman, M., Sapirstein, H., Shwedyk, E., Bushuk, W., 1987. Discrimination of wheat class and variety by digital image analysis of whole grain samples. J. Cereal Sci. 6 (2), 125–132. http://dx.doi.org/10.1016/S0168-1699(00)00152-6.

Nowak, E., Jurie, F., Triggs, B., 2006. Sampling strategies for bag-of-features image classification. In: Leonardis, A., Bischof, H., Pinz, A. (Eds.), Computer Vision–ECCV 2006. Springer, Berlin, Heidelberg, pp. 490–503. http://dx.doi.org/10.1007/11744085_38.

Özkan, K., Ergin, S., Işık, Ş., Işıklı, İ., 2015. A new classification scheme of plastic wastes based upon recycling labels. Waste Manage. 35, 29–35. http://dx.doi.org/10.1016/j.wasman.2014.09.030.

Pazoki, A., Pazoki, Z., 2013. Classification system for rain fed wheat grain cultivars using artificial neural network. Afr. J. Biotechnol. 10 (41), 8031–8038. http://dx.doi.org/10.5897/AJB11.488.

Peña, R., 2002. Wheat for bread and other foods, bread wheat improvement and production. In: Curtis, B.C., Rajaram, S., Gómez, M.H. (Eds.), Food and Agriculture Organization of the United Nations, Rome, pp. 483–542.

Philbin, J., Chum, O., Isard, M., Sivic, J., Zisserman, A., 2007. Object retrieval with large vocabularies and fast spatial matching. Comput. Vis. Pattern Recogn. 2007, 1–8. http://dx.doi.org/10.1109/CVPR.2007.383172.

Romero, J.R., Roncallo, P.F., Akkiraju, P.C., Ponzoni, I., Echenique, V.C., Carballido, J.A., 2013. Using classification algorithms for predicting durum wheat yield in the province of Buenos Aires. Comput. Electron. Agric. 96, 173–179. http://dx.doi.org/10.1016/j.compag.2013.05.006.

Ronge, R., Sardeshmukh, M., 2014. International Conference on Advances in Computing, Communications and Informatics (ICACCI 2014). IEEE, pp. 937–942. http://dx.doi.org/10.1109/ICACCI.2014.6968483.

Ruiz-Pinales, J., Acosta-Reyes, J., Salazar-Garibay, A., Jaime-Rivas, R., 2006. Shift invariant support vector machines face recognition system. Trans. Eng., Comput. Technol. 16 (2), 167–171.

Sapirstein, H., Kohler, J., 1999. Effects of sampling and wheat grade on precision and accuracy of grain features determined by digital image analysis. Cereal Chem. 76 (1), 110–115. http://dx.doi.org/10.1094/CCHEM.1999.76.1.110.

Shouche, S., Rastogi, R., Bhagwat, S., Sainis, J.K., 2001. Shape analysis of grains of Indian wheat varieties. Comput. Electron. Agric. 33 (1), 55–76. http://dx.doi.org/10.1016/S0168-1699(01)00174-0.

Vedaldi, A., Fulkerson, B., 2010. VLFeat: an open and portable library of computer vision algorithms. In: Proceedings of the International Conference on Multimedia. ACM, New York, pp. 1469–1472. http://dx.doi.org/10.1145/1873951.1874249.

Vedaldi, A., Zisserman, A., 2012. Efficient additive kernels via explicit feature maps. IEEE Trans. Pattern Anal. Mach. Intell. 34 (3), 480–492. http://dx.doi.org/10.1109/TPAMI.2011.153.

Wallach, H.M., 2006. Topic modeling: beyond bag-of-words. In: Proceedings of the 23rd International Conference on Machine Learning. ACM, New York, pp. 977–984. http://dx.doi.org/10.1145/1143844.1143967.

Zapotoczny, P., Zielinska, M., Nita, Z., 2008. Application of image analysis for the varietal classification of Barley: morphological features. J. Cereal Sci. 48 (1), 104–110. http://dx.doi.org/10.1016/j.jcs.2007.08.006.

Zayas, I., Pomeranz, Y., Lai, F., 1985. Discrimination between Arthur and Arkan wheats by image analysis. Cereal Chem. 62 (6), 478–480.

Zayas, I., Lai, F., Pomeranz, Y., 1986. Discrimination between wheat classes and varieties by image analysis. Cereal Chem. 63 (1), 52–56.

Zayas, I., Pomeranz, Y., Lai, F., 1989. Discrimination of wheat and nonwheat components in grain samples by image analysis. Cereal Chem. 66 (3), 233–237.

Zhou, H., Yuan, Y., Shi, C., 2009. Object tracking using SIFT features and mean shift. Comput. Vis. Image Underst. 113 (3), 345–352. http://dx.doi.org/10.1016/j.cviu.2008.08.006.