ISSN No:-2456-2165

Application of Image Processing for Classification and Quality Evaluation of Wheat

Mostafa Khojastehnazhand
Department of Mechanical Engineering University of Bonab,
Bonab, 5551761167, Iran

Abstract:- Wheat is one of the most important foods in the world. Classification of different wheat varieties and determination of quality parameters of wheat are an important challenge for the food grain industry all over the world. In the recent years, image processing technique as a none-destructive, rapid and automated method has acceptable accuracy of classification and qualification of wheat. In this review, recent research about classification of different varieties, damaged and sprouted kernels detection and vitreous and none-vitreous kernels detection of wheat by using image processing technique were collected. The results of different researches, shows high efficiency of machine vision technique.

***Keywords**:- wheatt; image processing; machine vision; classification; vitreous.*

I. INTRODUCTION

Wheat (Triticum aestivum) is one of the world's most consumed agricultural products by humans and livestock, planted in most countries of the world. This product is compatible with different ground conditions, including irrigated and dry land fields. Wheat after corn is one of the eight known cereals that are produced to feed billions of humans and animals [1]. The global production of wheat was 698 million metric tons in crop year 2015/2016 [2]. Detection and differentiation of different varieties of wheat has always been a major challenge for activists in this industry to achieve quality control and product grading policies. Each wheat variety is used as primary ingredients for specific products such as bread, cakes, cookies, pastries, crackers, pasta, flat bread, and noodles. Commercially, wheat is divided into three different categories by considering grain hardness (soft, medium-hard and hard), appearance (color, degree of damage by insects or fungi, shriveling, shape of embryo) and 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. Quality of wheat grains is a complex phenomenon influenced by several factors, genetic and/or environmental. It is usually judged by evaluation of some parameters such as the grain virtuousness, protein content, gluten content, etc. [3].

In the other hand, as human societies grow, the supply chain and distribution of food are also larger and more complex. Which has led food security decision makers to face a huge challenge in food fraud [4-7]. During the past decade, the demand for organically produced food has increased significantly [8]. Traditional methods used to classification and quality evaluation of wheat are manual, time consuming and subjective to personal decision. Each individual inspector produces different results based on her/his condition such as fatigue and eyesight, mental state caused by improper working condition [9]. Digitalized image analysis may be an advantageous method to distinguish varieties of different grain species. In the recent years, some researches were done to develop automated systems to classification and quality feature determination of wheat kernels. Machine vision is one of the best nondestructive methods to enhance the quality of products in the producing line in the factory. Machine Vision (MV) is the method used to provide image process-based technology for automatic inspection and analysis of different products. MV systems consist of imaging unit, illumination equipment, processing unit and imaging box. The imaging section includes cameras with the desired specification. Based on the application of MV, different camera such as CCD, thermal and hyperspectral camera can be used. The main part of a MV system is the image processing sector, which includes different pre-processing and modeling methods for linking real values and extracted values from the image. Many articles have been presented in the field of identification of grain characteristics, including color, texture and various types of damage, using image processing and analytical methods. [10-13].

In this review, recent applications of image processing technique to classification, Vitreous and none-vitreous and damaged kernel determination of wheat were discussed.

A. Classification

The quality of wheat grains depends on several parameters. The most important of which is the uniformity of the grains in terms of variety and type of wheat. The purity of wheat is affecting the purchase price of the product. The purity of wheat grains is reduced by factors such as the mixing of different varieties of wheat, broken grains and damaged grains by insect, germinated grains, weed seeds and foreign materials. Reference [14] for the first time, were used morphological properties for classification of wheat, based on U.S. market classes. Another researches was done for classification of different Canadian wheats using color processing [15-18]. Researchers reported that, the connection of kernels in the images is one of the most important challenges for image processing experts. Reference [19] developed an algorithm to separate connected kernels of hard red spring (HRS) wheat and kernels of durum wheat. The algorithm was successful in disconnecting kernels of HRS and durum wheat with accuracies of 95% [19]. In the other hand, some researches were done on individual grains for classification by using image processing algorithm. They classified individual kernels of Canada Western Red Spring

(CWRS) wheat and Canada Western Amber Durum (CWAD) wheat using textural features [20]. Reference [21] examined morphological and texture features of RGB color images to distinguish CWRS wheat and CWAD wheat using a back propagation neural network model as well as a non-parametric model. They determined the benefit of combining morphological and textural features in classification, achieving accuracies of >96%. They also developed a model to determination of dockage such as broken wheat kernels, chaff, buckwheat, wheat spikelet's, and canola in the same grain types, and again found that the ability to recognize dockage was acceptable [22]. Table I shows recent researches for classification of wheat using image processing. As shown, the accuracy of developed systems, depend on the number of selected features, the number of varieties, and selection of modeling. In most studies, the neural network method has been used for modeling. As a general conclusion, the machine vision method has a great ability to classify wheat.

B. Vitreousness

One of the important factors in determining the functionality of wheat varieties is the hardness of kernels. The hardness of wheat, as a qualitative feature, is used to determine the suitability of wheat varieties for flour and bread preparation. This factor, also is related to protein content and the flour water absorption [38]. Among the wheat varieties, durum wheat has a very hard endosperm that produce large chunks during milling. Based on the chunk size, these endosperm chunks are used to produce semolina or couscous. On the other hand, nonvitreous durum wheat kernels give a higher yield of flour in comparison to semolina during milling. So, determination of vitreous and nonvitreous kernels is important in milling industry. Vitreousness is a key important quality parameter used for classification of durum wheat. Vitreous durum wheat kernels has a clear, glassy and translucent appearance but nonvitreous kernels has a starchy and mottled appearance. Nowadays, classification of wheat based on vitreous kernel content is done visually by inspectors. This method is somewhat subjective, expensive, time consuming, tedious and it cannot be applicable in the producing line [39]. Machine vision is used as a non-destructive method to overcome the disadvantages mentioned in recent years. Researchers have used transmitted light images [40], transmitted and reflected light images for classifying vitreousness in durum wheat [41-42].

Table II shows recent publication of image processing application for vitreous detection of wheat. As shown in table II, the accuracy of machine vision technique is acceptable. Also, the reflection and transmitted images has more application in relation to the classification.

Variety	Mode	Model	accuracy	Ref.
Canadian Western Amber Durum (CWAD)	-	linear Bayesian classifier	-	[40]
hard and vitreous of amber color (HVAC) and not hard and vitreous of amber color (NHVAC)	reflectance and transmittance images	stepwise discriminant analysis and an artificial neural network (ANN)	91.0-94.9%	[41]
durum wheat	reflected, side-transmitted, and transmitted	ANN	100% for non-vitreous kernels and 92.6% for mottled kernels	[42]
durum wheat	reflected and transmitted images	Bayesian classifier	86%	[43]
durum wheat	X-rays or transmitted light	Bayesian classifier	76-82% (soft X-ray) 86-93% (transmitted light system)	[39]
durum wheat	trans-illuminated image	stepwise LDA and Bayesian classifier	96.03%	[9]

Table 1. Classification of Wheat Using Image Processing

ISSN No:-2456-2165

Variety	Feature	Model	Accuracy	Ref.
Hard Red Winter, Soft Red Winter and Hard Red Spring	-	-	77–85%	[14]
Six Canadian wheat classes	shape features and Fourier descriptors	-	15–96% for the identification of different varieties,	[23]
Soft White Winter (SWW), Hard Red Winter (HRW) and Hard Red Spring (HRS)	morphological features	four-way linear discriminant	64–100%	[16]
five Australian wheat varieties	size and shape features	-	44–96%	[24]
six Canadian wheat classes	mean red (R), green (G) and blue (B) pixel reflectance (tristimulus) features	Pairwise discrimination	34–90%	[18]
two Canadian wheat classes	three attributes viz. length, shape function and color	-	100% and 94%r	[25]
Turkish bread and durum wheat cultivars	morphological properties and color	-	98-99%	[26]
three wheat classes	45 morphological features	artificial neural network (ANN)	84-94%	[27]
two Canadian wheat classes	123 colour, 56 textural features and 51 morphological features	Statistical classifiers and a back propagation neural network	For bulk sample ≥87% For individual kernel ≤68%	[28]
eight western Canadian wheat	32 textural features	quadratic discriminant	92-94.4%	[29]
2 Canadian wheat classes	Morphological, colour, textural, and wavelet features	Linear and quadratic statistical classifiers	99.4% and 89.4%	[30]
spring and winter wheat	texture in seven channel	discriminant analysis and ANN	100%	[31]
wheat	99 features	discriminant analysis (DA) and K-nearest neighbors (K-NN)	higher than 99%	[32]
nine common Iranian wheat	131 textural features	linear discriminate analysis	98.15%	[33]
six classes of rain fed wheat	21 statistical features	Multi-Layer Perceptron (MLP) Neural Network	86.48% - 87.22%	[34]
four local wheat grades of Sardari variety	52 color, morphology, and texture characteristic parameters	Imperialist Competitive Algorithm (ICA) combined with (ANNs)	77.22-96.25%	[35]
four Indian wheat seed varieties	131 textural features	ANN and K-NN classifiers	66.68%	[36]
Turkish bread and durum wheat cultivars	Dense Scale Invariant Features	k-means clustering	88.33%	[37]

Table 2. Vitreous and non-Vitreous detection of wheat using image processing

C. Damaged Kernels

Based on food safety and massive market profits, a technique with a high-efficiency is necessary to improve the produced wheat quality. Providing a high quality product, including a product without damage by insects or fungi along with the product without contaminants [44]. The contaminants include foreign materials, dockage, and animal excreta. The presence of these contaminants affects the wheat quality and economic value. Foreign material can include damaged kernels of wheat, ergot, animal excreta, other cereals (such as barley, maize, rye, oats, and triticale), oat groats, and wild oat groats. Dockage is any material mixed with wheat which can be removed using specified cleaning units [45]. In general, items that can cause wheat mixed with other types of grain are: 1) Inappropriate cleaning of wheat silos, 2) Inappropriate cleaning of equipment and transportation vehicles, 3) improper weed control during production, and 4) the disability of the cleaning equipment to remove similar- sized grains. Contaminants are the major impurities in cereal grains.

In the recent year, a high- speed digital imaging system was used to detect damaged U.S. grown kernels in freefall. Two LDA and KNN classification models were used to determine the image features of fifty samples of hard red and white wheat subjected to weather-related damage. The damaged kernels consist of mold, pre-harvest sprouting, and black tip kernels. Area, projected volume, perimeter, ellipse eccentricity, and major and minor axis lengths of each kernel as morphological features and contrast, correlation, energy and homogeneity of gray level co-occurrence matrices as well as entropy of kernels as textural features were used in classification. The results indicate that with a combination of two morphological and four texture properties, classification levels attain 91–94% accuracy, depending on the type of classification model (LDA or KNN) [46]. Sprout damaged wheat grains is an important problem in the world. Damaged wheat kernels contain an enzyme called alpha-amylase that has low poor baking qualities. Quantification of this enzyme helps classification of wheat with different levels of sprout damage.

Table 3 shows recent researches about damaged kernel detection of wheat using image processing. As shown in table 3, the models accuracy for detection of damaged and sprouted kernels are acceptable.

Damage	Variety	Feature	Model	accuracy	Ref.
damage caused by Fusarium scab infection	Hard red spring wheat	55 color and texture features	artificial neural network	97%	[47]
Insect detection in wheat	-	-	Statistical multivariate analysis	90%	[48]
Damaged Kernels	Canada Western Red Spring wheat	morphological properties and color	linear discriminant analysis, (LDA) and k-nearest neighbor, (KNN)	90–100%	[11]
Dockage Identification	Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat	51 morphological, 123 colour, and 56 textural	neural network	90%	[49]
Infestations detect	-	57 features	statistical classifiers and back propagation neural network (BPNN)	73-86%	[50]
SPROUTED WHEAT detection	-	55 image features	statistical and neural network classifiers	90-95%	[51]
SPROUTED WHEAT DETECTION	-	Sixteen features comprising of colour, texture, and shape and size	ANN	72.8%	[52]

Table 3. Damaged Kernels detection of wheat by using image processing

II. CONCLUSION

Image processing technique as a none-destructive, rapid and automated method has a high performance in classification and quality parameter determination of wheat. The results accuracy is affected by the number of selected features, the modeling method and the similarity of the classes. Based on research, image processing can be used as an acceptable method for improving the quality of wheat used in humans and animal alteration. The only challenge that many researchers are involved with is the separation and recognition of interlocking grains, which will require more research to provide new and powerful algorithms in this field.

REFERENCES

[1]. FAS, "United States Department of Agriculture" 2007, <http://www.fas.usda.gov> Available at: (accessed 12.12.08).

[2]. Statista, The statatistic portal 2015, www.statista.com.

[3]. V. Sardana, "Grain quality of wheat as influenced by application of nitrogen, climate and cultural practices: a review," Agricultural Reviews, 2000, 21(2), pp. 116-120.

[4]. M. Ottavian, L. Fasolato, L. Serva, P. Facco, and M. Barolo, "Data fusion for food authentication: fresh/frozen–thawed discrimination in West African Goatfish (Pseudupeneus prayensis) fillets," Food and bioprocess tech., 2014, 7(4), pp. 1025-1036.

[5]. L. Huang, H. Liu, B. Zhang, and D. Wu, "Application of electronic nose with multivariate analysis and sensor selection for botanical origin identification and quality determination of honey," Food and Bioprocess Tech., 2015, 8(2), pp.359-370.

[6]. S.N. Jha, P. Jaiswal, A. Borah, A.K. Gautam, and N. Srivastava, "Detection and quantification of urea in milk using attenuated total reflectance-Fourier transform infrared spectroscopy," Food and Bioprocess Tech., 2015, 8(4), pp.926-933.

[7]. J. Qin, K. Chao, M.S. Kim, and B.K. Cho, "Line-scan macro-scale raman chemical imaging for authentication of powdered foods and ingredients," Food Bioprocess Technol., 2016, 9 (1), pp. 113-123.

[8]. C. David, J. Abecassis, M. Carcea, F. Celette, J. Friedel, G. Hellou, and, J. Peigne, "Organic bread wheat production and market in europe sustainable agriculture reviews," Springer, 2012, pp. 43-62.

[9]. G. Venora, O. Grillo, and R. Saccone, "Quality assessment of durum wheat storage centres in Sicily: evaluation of vitreous, starchy and shrunken kernels using an image analysis system," J. cereal Sci., 2009, 49(3), pp. 429-440.

[10]. L. Bacci, B. Rapi, F. Colucci, and P. Novaro, “Durum wheat quality evaluation software,” In: Proc. The World Congress of Computers in Agriculture and Natural Resources, ASAE, St. Joseph, Mich., 2002, pp. 49–55.

[11]. X. Luo, D.S. Jayas, and S.J. Symons, “Identification of damaged kernels in wheat using a colour machine vision system,” J. Cereal Sci., 1999, 30, pp. 49–59.

[12]. R. Ruan, S. Ning, L. Luo, P. Chen, R. Jones, W. Wilcke, and V. Morey, “Estimation of weight percentage of scabby wheat kernels using an automatic machine vision and neural network based system,” Trans ASAE, 2001, 44 (4), pp. 983–988.

[13]. I.Y. Zayas, D.B. Bechtel, J.D. Wilson, and R.E. Dempster, “Distinguishing selected hard and soft red winter wheat by image analysis of starch granules,” Cereal Chem., 1994, 71 (1), pp. 82–88.

[14]. I. Zayas, F.S. Lai, and Y. Pomeranz, “Discrimination between wheat classes and varieties by image analysis,” Cereal Chem., 1986, 63, pp. 52–56.

[15]. H.D. Sapirstein, M.R. Neuman, E.H. Wright, E. Shwedyk, and W. Bushuk, “An instrumental system for cereal grain classification using digital image analysis,” J. Cereal Sci, 1987, 6, pp. 3–14.

[16]. S.J. Symons, and R.G. Fulcher, “Determination of wheat kernel morphological variation by digital image analysis: I. Variations in eastern Canadian milling quality wheats,” J. Cereal Sci., 1988, 8, pp. 211–218.

[17]. M.R. Neuman, H.D. Sapirstein, E. Shwedyk, and W. Bushuk, “Wheat grain color analysis by digital image processing. I. Methodology,” J. Cereal Sci., 1989, 10, pp. 175–182.

[18]. M.R. Neuman, H.D. Sapirstein, E. Shwedyk, and W. Bushuk, Wheat grain color analysis by digital image processing. II. Wheat class discrimination. J. Cereal Sci., 1989, 10, pp. 183–188.

[19]. P. Shatadal, D.S. Jayas, and N.R. Bulley, “Digital image analysis for software separation and classification of touching grains. II. Classification,” Trans. ASAE, 1995, 38, pp. 645–649.

[20]. S. Majumdar, and D.S. Jayas, “Classification of cereal grains using machine vision: III. Texture models,” Trans ASAE, 2000, 43, pp. 1681–1687.

[21]. J. Paliwal, N.S. Visen, D.S. Jayas, and N.D.G. White, “Comparison of a neural network and non-parametric classifier for grain kernel identification,” Biosys. Eng. 2003, 85, 405–413.

[22]. J. Paliwal, N.S. Visen, D.S. Jayas, and N.D.G. White, Cereal grain and dockage identification using machine vision. Biosys. Eng., 2003, 85, pp. 51–57.

[23]. M.R. Neuman, H.D. Sapirstein, E. Shwedyk, and W. Bushuk, “Discrimination of wheat class and variety by digital image analysis of whole grain samples,” J. Cereal Sci., 1987, 6, pp. 125–132.

[24]. D.G. Myers, and K.J. Edsall, “The application of image processing techniques to the identification of Australian wheat varieties,” Plant Varieties and Seeds, 1989, 2, pp.109–116.

[25]. J. Paliwal, N.S. Shashidhar, and D.S. Jayas, “Grain kernel identification using kernel signature,” Trans ASAE, 1999, 42(6), pp.1921.

[26]. H. Utka, “Application of the feature selection method to discriminate digitized wheat varieties,” J. Food Eng., 2000, 46, pp. 211–216.

[27]. B.P. Dubey, S.G. Bhagwat, S.P. Shouche, and J.K. Sainis, “Potential of artificial neural networks in varietal identification using morphometry of wheat grains,” Biosys. Eng., 2006, 95, pp. 61–67.

[28]. A.R. Tahir, S. Neethirajan, D.S. Jayas, M.A. Shahin, S.J. Symons, and N.D.G. White, “Evaluation of the effect of moisture content on cereal grains by digital image analysis,” Food Res. Int., 2007, 40(9), pp. 1140-1145.

[29]. A. Manickavasagan, G. Sathya, D.S. Jayas, and N.D.G. White, “Wheat class identification using monochrome images” J. cereal Sci., 2008, 47(3), pp.518-527.

[30]. R. Choudhary, J. Paliwal, and D.S. Jayas, “Classification of cereal grains using wavelet, morphological, colour, and textural features of non-touching kernel images,” Biosystems Eng., 2008, pp 99, 330–337.

[31]. P. Zapotoczny, “Discrimination of wheat grain varieties using image analysis and neural networks. Part I. Single kernel texture,” J. Cereal Sci., 2011, 54(1), pp. 60-68.

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

[33]. A. Pourreza, H. Pourreza, M.H. Abbaspour-Fard, and H. Sadrnia, “Identification of nine Iranian wheat seed varieties by textural analysis with image processing,” Computers and electronics in Agri., 2012., 83, pp. 102-108.

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

[35]. E. Ebrahimi, K. Mollazade, and S. Babaei, “Toward an automatic wheat purity measuring device: A machine vision-based neural networks-assisted imperialist competitive algorithm approach,” 2014, Measurement, 55, pp.196-205.

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

[37]. M. Olgun, A.O. Onarcan, K. Özkan, Ş. Işik, O. Sezer, K. Özgişi, N.G. Ayter, Z.B. Başçiftçi, M. Ardiç, and O. Koyuncu, “Wheat grain classification by using dense SIFT features with SVM classifier,” Comp. and Elec. in Agri., 2016, 122, pp.185-190.

[38]. J.E. Dexter, B.A. Marchylo, A.W. MacGregor, and R. Tkachuk, “The structure and protein composition of vitreous, piebald and starchy durum wheat kernels,” J. Cereal. Sci. 1989, 10, 19–32. Dobraszczyk,

ISSN No:-2456-2165

[39]. S. Neethirajan, C. Karunakaran, S. Symons, and D.S. Jayas, "Classification of vitreousness in durum wheat using soft X-rays and transmitted light images," Computers and electronics in Agri., 2006, 53(1), pp.71-78.

[40]. S.J. Symons, L. Van Schepdael, and J.E. Dexter, "Measurement of hard vitreous kernels in durum wheat by machine vision," Cereal Chem., 2003, 80 (5), pp. 511–517.

[41]. F., Xie, T. Pearson, F.E. Dowell, and N. Zhang, "Detecting vitreous wheat kernels using reflectance and transmittance image analysis," Cereal chem., 2004, 81(5), pp.594-597.

[42]. N. Wang, N. Zhang, F.E. Dowell, and T. Pearson, "Determining vitreousness of durum wheat using transmitted and reflected images," Trans ASAE, 2005, 48 (1), pp. 219–222.

[43]. M.A. Shahin, E. Dorrian, and S.J. Symons, "Machine vision system to detect hard vitreous kernels in durum wheat," Proc. CSAE/SCGR Annual Conference, Winnipeg, June, 2005.

[44]. W.H Su, and D.W. Sun, "Evaluation of spectral imaging for inspection of adulterants in terms of common wheat flour, cassava flour and corn flour in organic Avatar wheat (Triticum spp.) flour," J. Food Eng., 2017, 200, pp. 59-69.

[45]. CGC, "Official grain grading guide Wheat," August 1, Canadian Grain Commission Industry services, Canadian Grain Commission. Available from: https://www. grainscanada.gc.ca/oggg-gocg/2013/04-wheat-2013-eng.pdf Accessed 11.11.13.

[46]. S.R. Delwiche, I.C. Yang, and R.A. Graybosch, "Multiple view image analysis of freefalling US wheat grains for damage assessment," Comp. and Electronics in agri., 2013, 98, pp. 62-73.

[47]. R. Ruan, S. Ning, A. Song, A. Ning, R. Jones, and P. Chen, "Estimation of Fusarium scab in wheat using machine vision and a neural network," Cereal Chem., 1998, 75, pp. 455–459.

[48]. I.Y. Zayas, and P.W. Flinn, "Detection of insects in bulk wheat samples with machine vision," Trans. the ASAE, 1998, 41, pp. 883–888.

[49]. J. Paliwal, N.S. Visen, D.S. Jayas, and N.D.G., White, "Cereal grain and dockage identification using machine vision," Biosys. Eng., 2003, 85(1), pp. 51-57.

[50]. C. Karunakaran, D.S. Jayas, and N.D.G. White, "Identification of wheat kernels damaged by the red flour beetle using X-ray images," Biosyst. Eng., 2004, 87, pp. 267–274.

[51]. S. Neethirajan, D.S. Jayas, N.D.G. White, "Detection of sprouted wheat kernels using soft X-ray image analysis," J. Food. Eng., 2007, 81, pp. 509–513.

[52]. B.L. Shrestha, Y.M. Kang, D. Yu, and O.D. Baik, "A two-camera machine vision approach to separating and identifying laboratory sprouted wheat kernels," Biosys. Eng., 2016, 147, pp. 265-273.