Australian Journal of Crop Science
AJCS

AJCS 5(2):111-115 (2011) ISSN:1835-2707

An approach to estimate moisture content of apple with image processing method

Farshad Vesali*[1], Masoud Gharibkhani[2] and Mohmmad Hasan Komarizadeh[3]

[1]**Department of Mechanic of Agricultural Machinery Engineering, Urmia University of Urmia, Iran**
[2]**Islamic Aazad University, Astara Branch, Young Researchers Club, Astara, Iran**
[3]**Department of Mechanic of Agricultural Machinery Engineering, Urmia University of Urmia, Iran**

[*]**Corresponding author: f.vesali@live.com; st_f.vesali@urmia.ac.ir**

Abstract

Moisture content is an important quality feature that directly influences storability of fruits and vegetables. The main goal of the present study was to estimate moisture content of one variety of apple fruits (Golden Delicious) with image processing method. In five weeks duration, about 100 images of samples were taken and simultaneously the weight of each sample was measured and recorded. As we know, approximately 80 percent of apple is water, so decreasing moisture content of apples during time, has effective influence on density of them. In this study, image-processing method was used to obtain an index that portends the apples' density. Furthermore, wrinkles of some part of apples' skin were measured with IPM. To measure wrinkles, some texture analysis parameters were measured from one of main component of apple images. Without taking into consideration the texture analysis parameters, coefficient of determination (R^2) between measured density and moisture content was found about 0.74. When texture analysis parameters were used, a neural network was made which its inputs were texture analysis parameters and density index. The neural network estimated moisture content of apples with higher accuracy than the previous one (0.92). These procedures appeared to be a good method for the assessment of apples' moisture content, non-destructively.

Keyword: density index, moisture content, neural networks, texture analysis parameters, wrinkles.
Abbreviation: 3CCD- 3 Charged Coupled Device; ANN- Artificial neural network; CMY- Cyan, Magenta, Yellow; DI- Density Index; GD- Golden delicious; IPM- Image processing method; LMC- Lost Moisture Content; MC- Moisture Content; MSE- Mean Square Error; NIR- Near Infrared; NN- Neural network; R^2- Coefficient of Determination; RD- Red delicious; RGB- Red, Green, Blue.

Introduction

The use of image processing method as a nondestructive method for sorting and identification of damages in fruits is increasing now a days. As apple is a strategic fruit in vegetable and fruit marketing, lots of researches have been done in relation to it. Shahin et al. (2002) used Line–scan x–ray imaging and Artificial neural network to distinguish the bruise damage of two variety of apples (Red delicious and GD), for separating damaged apples from others. They made two ANNs, one for new bruises (24 hours) and one for old bruises (one month) to separate apples. They achieved the accuracy between 60 and 90% for different varieties and bruises (old or new). Firmness, soluble solid content and titratable acidity, are three important indexes in apple quality for marketing (Harker et al., 2008). Regularly the destructive methods are used for determining the firmness and soluble solid content of apple. Nevertheless, in recent researches, researchers tried to predict important quality parameters of apple, like soluble solid content and firmness, non-destructively. Some different methods were used to estimate these parameters as Near Infrared spectroscopy and analysis of scattering images (Lu, 2003, 2004; Peng and Lu, 2006, 2007; Qing et al., 2008). Lu (2004) developed a new method for predicting the firmness of fruits by scattering Images with different light wave lengths in near infrared rang. In addition, the profiles of radial distributions were used as inputs of neural network that had good effects on estimating the firmness of apple. Also Noh et al. (2007) acquired reflectance and fluorescence scattering images using a hyperspectral image system for assessing apple maturity. To validate their own methods, they performed a distractive test for measuring multiple maturity parameters. They found that the fluorescence prediction models consistently had lower correlations with individual maturity parameters than the reflectance models however, integrated reflectance and fluorescence improved the correlation up to 12%. Another important element that affects consumers' decision is the MC of fruit. It is obvious that the higher MC of fruit, the fresher it looks (Harker et al. 2008). In addition, moisture loss during long-term storage of apple causes direct economic loss because of decrease in saleable weight. Excessive weight loss causes the fruit skin to shrivel or the wax structure to change and become greasy or glossy (Maguire et al. 1999). Veraverbeke et al. (2003) attempt, was undertaken to evaluate the specific effect of the cuticle structure with lenticels and cracks in the modeling of moisture loss during long-term storage and shelf life of apples. They estimated actual diffusion coefficients of tissue, cutin, and wax for the apple cultivars Jonagold and Elstar. This was done using a modeling approach with finite elements by means of geometrical models based on microscopic images of the cuticle. Romano et al. (2008) tested laser light backscattering imaging technique as a tool for monitoring MC, during drying of banana slices in three temperatures of 53, 58 and 63 centigrade. They observed that, the color of banana slices went brown as the time passed. By specifying color indexes for getting brown, the moisture index for slices' in these three temperatures were found by image processing method. Appraising MC is an important item, not only for determining fruits quality, but also in grain drying process. Chung and Verma (1991) used resistance – type moisture sensor for measuring rice MC during drying process. They expressed voltage of sensor as a function of grain moisture, grain temperature and their interaction. In another research Thomasson (1995) tried to measure cotton moisture by examining some sensors (a standard silicon-chip, charge-coupled device, infrared-sensitive, black-and-white video camera). However, all correlations that he found were weak. In some other studies for predicting MC of agriculture crops like peanut and Mazafati date, NIR spectroscopy technique was applied (Mireei et al., 2010 and Sundaram et al., 2009).

Materials and methods

Apple Samples

During experiments in current research, 30 apples of GD variety were used. The apples were collected from Urmia University orchards in harvesting season of 2008. Immediately after harvest, all the apples initial weight was recorded. Then 6 pieces of apples were kept in 50 centigrade degrees for 72 hours, to obtain total MC of apples. The others were kept in regular temperature (20-centigrade degrees) for 24 days. During these 24 days, the samples were weighted by digital balance with accuracy of 0.1 grams, for three times (once per eight days).

Image acquisition

For image capturing a three Charged Coupled Device (3CCD) camera (Sony cyber-shot W200) was used. The pictures were saved in RGB color space with 2048*1536 pixels size. In order to have the same calibration of dimension in all pictures, a box was designed to provide a fixed distance between camera and samples. In addition, this box was equipped to a lighting system to prepare same light condition.

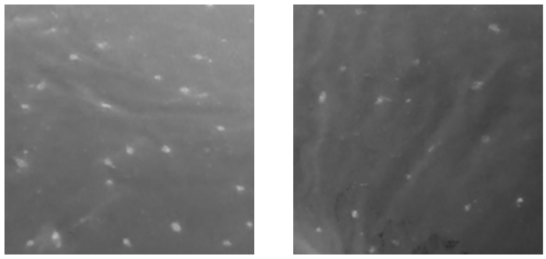
Obtaining MC with regular method

For measuring the MC and lost moisture content of apples, equation No.1 andNo.2 can be used respectively.

$$MC_{W,wb} = \frac{m_W}{m_{total}} \quad (1)$$

$$LMC = \frac{m_{pri\,(total)} - m_{sec}}{m_{total}} \quad (2)$$

Where MC_W is wet based moisture content, m_w is water mass, m_{total} is total mass, LMC is lost moisture content and m_{sec} is secondary mass of samples. MC of six samples was measured with standard oven test, representing all samples. For the other samples, in 24 days in three steps (once per 8 days), the LMC of samples was measured.



A B

Fig 1. Two pieces of M component of apples' Images with different LMC for determining texture analysis parameters

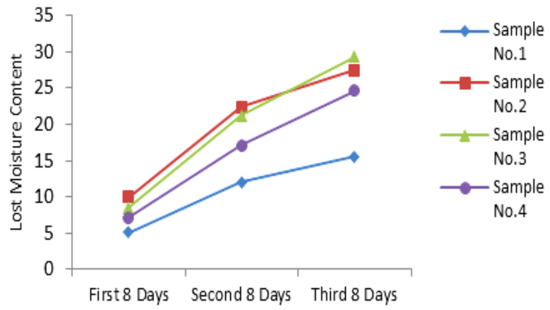


Fig 2. The procedure of losing MC of some samples in 24 day

The functions used in image processing

As samples' moisture decrease, no significant change in their dimension happened, but weight loss was obvious. The apple samples were assumed as sphere. By extracting the number of sample pixels from pictures, a factor of radius for density index was found. In fact, this index is a criterion for MC of samples. The decrease in samples' MC not only causes weight loss, but also leads to peel wrinkling, increase in inner hollows, change in cell structure and turgor pressure (Duprat et al., 1995). This structure change in fruit cells increases by MC reduction and as a result, more wrinkles will appear on fruit. In order to improve the accuracy, some texture parameters were obtained to measure the apple samples surface wrinkles. In order to specify the texture of surface, statistical approaches can be use (Gonzalez & Woods, 2008). For extracting these parameters, about 120 pieces of samples' surface were separated from images and the parameters were calculated after deleting the dark spots. These parameters consist of mean intensity, smoothness, uniformity, third momentum and entropy as equationsNo.3 toNo.7, show respectively.

$$I = \sum_{i=0}^{L-1} z_i p(z_i) \quad (3)$$

$$S = 1 - \frac{1}{1+\sigma^2} \quad (4)$$

$$\mu_3 = \sum_{i=0}^{L-1} (z_i - I)^3 p(z_i) \quad (5)$$

$$U = \sum_{i=0}^{L-1} p^2(z_i) \qquad (6)$$

$$e = -\sum_{i=0}^{L-1} p(z_i)\log_2 p(z_i) \qquad (7)$$

Where I is mean intensity, z_i is a random variable denoting intensity, $p(z_i)$, i=0,1,…, L-1, is the corresponding histogram, L is the number of distinct intensity levels, S is smoothness σ^2 is the variance, U is uniformity and e is entropy.

Due to the lower noise in G and M components in RGB and CMY color spaces, these components were better than others and as light reflection in M component was vice versa, this one was selected for determining texture analysis parameters. In Fig.1, two pictures of separated pieces are shown.

Estimation of LMC

For estimating the LMC two statuses were verified. In first status, only the density index was used for predicting LMC and correlation between density index and LMC was examined. But in second statue some perceptron neural networks were built with back propagation learning algorithm for precise measuring of MC, based on density index and texture parameter analysis. In other words density index and apple surface texture analysis parameters were inputs of NNs and the output of them was LMC. Low mean square error and lower number of hidden layers and neurons are the criteria for choosing neural network. By taking into consideration these touchstones; the structure of neural network was made. To prevent data saturation, before starting the training process the input values were normalized by using equation No.8

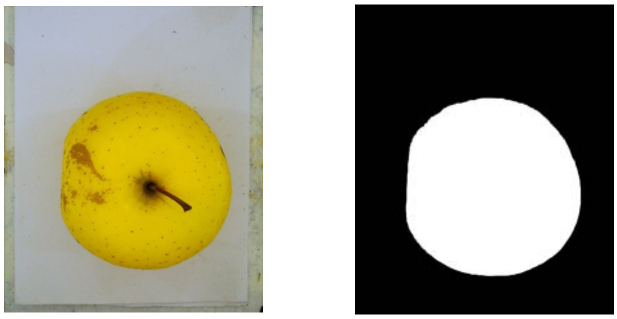
$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (8)$$

Where x, x_{min}, x_{max} and x_{norm} respectively are the real valued input variable, the minimum and maximum possible values of input data and it's normalized value. To get the real-valued output, the neural network output value needs to be denormalised according to the following equation:

$$y = y_{norm}(y_{max} - y_{min}) + y_{min} \qquad (9)$$

Results

The total moisture of apples after 72 hours in oven was about 83%. The measured LMC at first step (after 8 days), was between 3.2 - 10.4%, at second step (after 16 days) between 9.1 - 23.7 and at the third step between 15.5 - 31.4. Fig.2 shows the procedure of MC loss for 4 samples, representing all samples. The density index for LMC was obtained by both images processing and weighing. Fig. 3 is an example of segmenting apple from background to acquire radius factor of assumed sphere. This density index was able to estimate the LMC of samples with 0.78 in linear type and 0.80 in polynomial order 3 type, for R^2. In this research 80% of the data set was selected randomly for training neural networks. Predetermined values for the output error (MSE) and maximum iteration number were determined as 0.005 and 1000 epochs, respectively. Neural networks with one hidden layer and different number of neurons in this layer were



A B

Fig 3. An example Image from apple samples. A) Primary Image. B) The same image after segmentation.

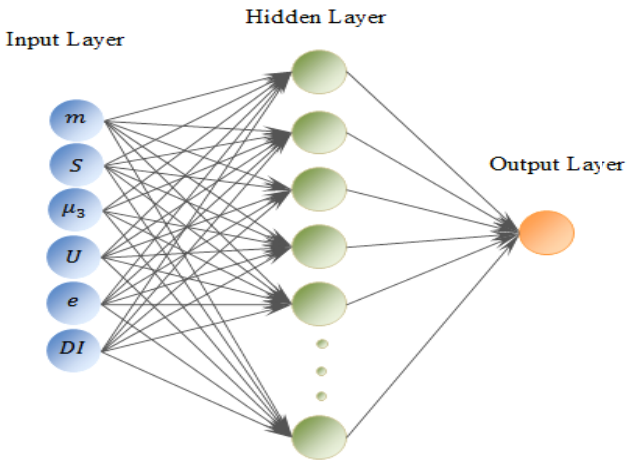


Fig 4. The schematic structure of Multi-Layer Perceptron Neural Networks model

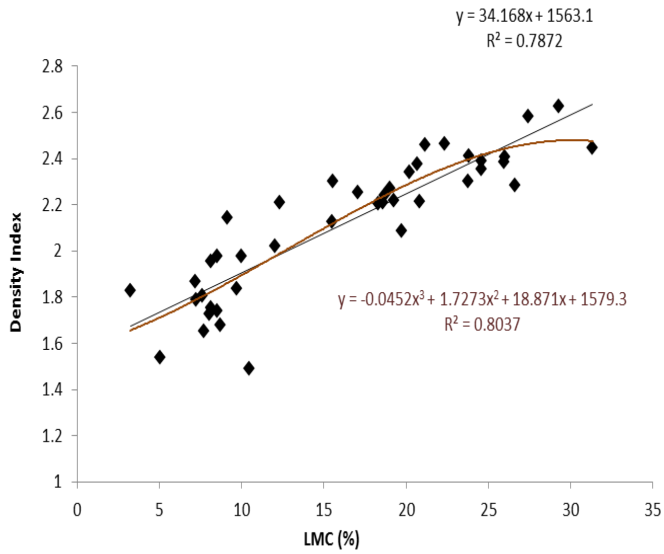


Fig 5. The LMC and density index correlation obtained by image processing

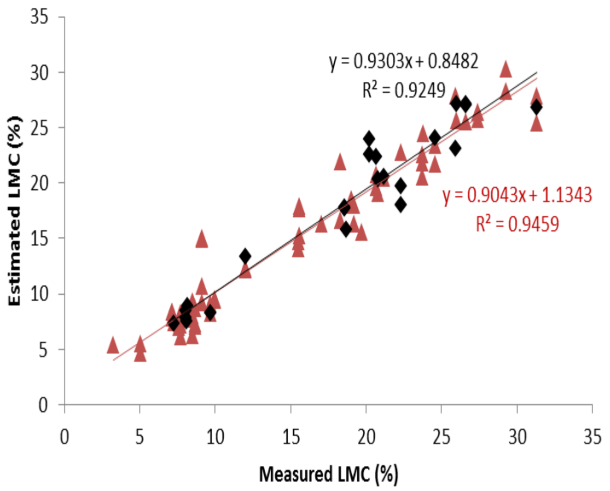


Fig 6. Correlation between estimated LMC with NN method and real LMC in training (▲) and testing (♦) step.

considered and finally selected neural network had 10 neurons in hidden layer with sigmoid transfer function in hidden layer and linear transfer function in output layer. The learning cycle was terminated in 426 iterations with an output error of 0.0049 for MSE (based on normalized value). Regression analysis of the estimated values by neural network model resulted in the following regression equation:

$$LMC_{est} = 0.9043 LMC_{meas} + 1.1343 \qquad (9)$$

Where LMC_{est} is estimated value and LMC_{meas} is measured value by equation no.2. To confirm the trained neural network, it was necessary to consider the neural network with unused data set. For this purpose, 20% of data (remained data) was used. R^2 value for the tested data was 0.92.

Discussion

The method that we used for measuring MC of apples is simpler than the methods that were used by Sudaram et al. (2009), Mireei et al. (2010) and Singh et al. (2004) for predicting MC of their samples. In this method, we just used a balance and an imaging device to estimate MC of apple and as mentioned in result section our method achieved a proper accuracy. Also Xiao et al. (2009) examined two methods for assessing MC of soil, NIR spectroscopy and machine vision. They found that HSV color space with BP neural networks is more accurate than NIR spectroscopy method. Correlation between LMC and density index is shown in fig.5. It also contains the trend line for linear and polynomial order 3 types. According to R^2 of linear and polynomial order 3, there is no considerable difference between them. As Veraverbeke et al. (2003) demonstrated moisture loss in 25 days causes the weight loss about 2.5 percent at relative humidity of 95%. In other words, it shows that density index can be a good parameter to estimate LMC of apples. At this step, the results are comparable with the results reported by Romano et al. (2008). They estimated MC of banana slices with backscattering area during drying process in three different temperatures (53ºc, 58ºc & 63ºc). Their results showed coefficient of determination of 0.72, 0.71 and 0.67 for mentioned temperatures respectively. Mireei et al. (2010) and Sudaram et al. (2009) achieved higher value for R^2, when they predict MC of Mazafati date and peanut. Correlation of NN's output in testing step with real LMC is shown in Fig.6. Increase accuracy in predicting MC with NN, is obvious (Increase in R^2 value from 0.80 to 0.92). This growth in R^2 may appear due to adding apples' surface texture parameters to density index as inputted data and high performance of NNs in predicting MC. It is apparent from Fig. 6 that the difference between LMC correlation in training and testing steps is low and it shows that training of NN was proper. R^2 of prediction with NN is close to results of Mireei et al. (2010) and Sudaram et al. (2009) which obtained 0.98 and 0.96 values of R^2 respectively.

Conclusion

The MC of fruit and vegetables is one of the important factors that have certain effect on their quality. In this research, a method was introduced that makes it possible to measure the MC of apple fruit by a simple balance and image processing, rapidly and non-destructively. Estimation of samples' LMC was assessed by two techniques, linear regression and neural networks. Linear regression showed a good correlation between density index and LMC of samples. However, in neural networks in addition to density index, some parameters which show surface wrinkles of apple were added to inputted data. Because of more inputs and NN essence, the second technique predicts the LMC of samples more accurately. Finally we can say that this method is a good way to estimate MC of apple and useful for apple sorting based on MC, after storing period.

References

Chung JH, Verma LR (1991) Measurement of Rice Moisture during Drying Using Resistance-Type Sensors. American Society of Agricultural Engineers 7(5): 630-635

Duprat F, Chen H, Grotte M (1995) Laser light based machine vision system for nondestructive ripeness sensing of Golden apples. Paper presented at 1st workshop of control applications in postharvest and processing technology, CAPPT

Gonzalez RC and Woods RE (2008). Digital Image Processing. Pearson Prentice Hall. New Jersey.

Harker FR, Kupferman EM, Marin AB, Gunson FA and Triggs CM (2008) Eating quality standards for apples based on consumer preferences. Postharvest Biology and Technology 50: 70–78

Lu R (2003) Near-infrared multispectral scattering for assessing internal quality of apple fruit. SPIE Proc 5271: 313–320.

Lu, R. (2004). Multispectral Imaging for Predicting Firmness and Soluble Solids Content of Apple Fruit. Postharvest Biology and Technology 31(2): 147–57.

Maguire KM, Lang A, Banks NH, Hall A, Hopcroft D, Bennett R, (1999) Relationship between water vapour permeance of apples and microcracking of the cuticle. Postharvest Biology and Technology (17): 89-96.

Mireei SA, Mohtasebi SS, Massudi R, Rafiee1Sh, Arabanian AS, Berardinelli A (2010) Non-Destructive Measurement of Moisture and Soluble Solids Content of Mazafati Date Fruit by NIR Spectroscopy. Aust J Crop Sci 4(3):175-179

Noh HK, Peng Y, Lu R (2007) Integration of Hyperspectral Reflectance and Fluorescence Imaging for Assessing Apple Maturity. Transactions of the ASABE 50(3): 963−971

Peng, Y. Lu, R (2006) Improving apple fruit firmness prediction by effective correction of multispectral scattering images. Postharvest Biology and Technology, 41(3): 266–274.

Peng, Y. Lu, R (2007) Prediction of apple fruit firmness and soluble solids content using characteristics of multispectral scattering images. Journal of Food Engineering 82: 266–274.

Qing Z, Ji B, Zudeb M (2008) Non-destructive analyses of apple quality parameters by means of laser-induced light backscattering imaging. Postharvest Biology and Technology 48: 215–222

Romano G, Baranyai L, Gottschalk K and Zude M (2008) An Approach for Monitoring the Moisture Content Changes of Drying Banana Slices with Laser Light Backscattering Imaging. Food Bioprocess Technology I: 410–414.

Shahin MA, Tollner EW, McClendon RW, Arabnia HR (2002) Apple Classification Based On Surface Bruises Using Image Processing and Neural Networks. Transactions of the ASAE 45(5): 1619-1627.

Singh B,Wang N, Prasher S, Ngadi M (2004) A Spectroscopic Technique for Water Content Determination in Potato. Paper presented at ASABE Annual International Meeting. Ottawa Ontario Canada, 1 - 4 August.

Sundaram J, Chari VK, Christopher LB, William RW (2009) Application of NIR Reflectance Spectroscopy on Determination of Moisture Content of Peanuts: A Non-Destructive Analysis Method. Paper presented at ASABE Annual International Meeting. Reno, Nevada, June 21 – June 24

Thomasson JA (1995) Cotton Moisture Measurement with a Black-and-White Video Camera. American Society of Agricultural Engineers 11(3): 371-375

Veraverbeke EA, Verboven P, Van Oostveldt P, Nicolaï BM (2003) Prediction of moisture loss across the cuticle of apple [*Malus sylvestris* subsp. mitis (Wallr.)] during storage: part 2: Model simulations and practical applications. Postharvest Biology and Technology 30: 75-88.

Xiao W, Li X, Li P, Elbashir MA, Wei W, Yaoze F (2009) Research on soil moisture Detection based on data fusion of near-infrared spectroscopy and machine vision. Paper presented at ASABE Annual International Meeting. Reno, Nevada, June 21 – June 24