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Araştırma Makalesi (Research Article)

Design of Real Time Image Processing Machine for Carrot Classification**

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Abstract: Kasınhanı district of Konya province has the greatest carrot production in Turkey. By the year 2017, Konya Province has approximately 46.5% of carrot production areas and 59.7% of total production. There are several washing and packing facilities in the region. These facilities show totally similar features and fully satisfy the needs of the region. Carrots coming from the washing pools come firstly to the mechanical grading machines and then to the packing department or directly to the packing department in some facilities. Grading and packing processes are carried out manually in these facilities. The classification efficiency of mechanical classification machines is known to be insufficient. In this study, mechanical, electronic and software sections of the real-time image processing machine are explained. The system was composed of a belt conveyor, cameras and closed chamber to receive images, image processing and control computer and routing covers attached to servo motors. As a result of the experiments, carrot classification rates ranged from 80.14 to 100% in real-time image processing machine.

Havuç Sınıflandırması için Gerçek Zamanlı Görüntü İşleme Makinesi Tasarımı

Öz: Konya ili Kasınhanı ilçesi, Türkiye'nin en büyük havuç üretimine sahiptir. 2017 yılında Konya ili havuç üretim alanlarının yaklaşık% 46.5'ine ve toplam üretimin% 59.7'sine sahiptir. Bölgede birkaç yıkama ve paketleme tesisi bulunmaktadır. Bu tesisler tamamen benzer özellikler sergilemekte vei bölgenin ihtiyaçlarını tam olarak karşılamaktadır. Yıkama havuzlarından gelen havuçlar önce mekanik sınıflandırma makinelerine, daha sonra paketleme bölümüne veya bazı tesislerde yıkamadan direk paketleme bölümüne gelir. Sınıflandırma ve paketleme işlemleri bu tesislerde elle yapılır. Mekanik sınıflandırma makinelerinin sınıflandırma verimliliğinin yetersiz olduğu bilinmektedir. Bu çalışmada, gerçek zamanlı görüntü işleme makinesinin mekanik, elektronik ve yazılım bölümleri açıklanmıştır. Sistem bir bant konveyörü, kameralar ve görüntüleri almak için kapalı odadan, görüntü işleme ve kontrol bilgisayarı ve servo motorlara bağlı yönlendirme kapaklarından oluşmuştur. Deneyler sonucunda, gerçek zamanlı görüntü işleme makinesinde havuç sınıflandırma oranları % 80.14 ile % 100 arasında değişmektedir.

1. Introduction

Carrot is a root vegetable which belongs to *Daucus carota* L. species of Umbelliferae family. Carrot is the second root vegetable grown worldwide after potato. China is the leading carrot producer country of the world. While the annual carrot and turnips production worldwide was 20.37 million tons in the year 2017, Turkey met about 1.33% of such annual production. Turkey has the 9th place with this production in the world (Anonymous, 2017).

It is commonly grown in various parts of the world including Turkey. Almost all of the carrots produced worldwide have relatively orange color. Nantes, Chantenay, Imperial, Danvers and Little finger are the most common cultivars throughout the world. Nantes is the mostly produced cultivar in Turkey.

Hatay, Ankara and Konya provinces are the significant carrot production districts of Turkey. In Konya region, carrot production was performed over 93 200 da land area in the year 2017 and the province had the first place with 527 000 tons of production in the country. Konya Province has approximately 46.5% of carrot production areas and 59.7% of total production (Anonymous, 2019).

Together with increasing world population, classification and packing of agricultural commodities have become significant issues. Following the transportation of produce from the field to packing facilities, they need to be classified based on various inherent criteria. Classification and packing of products based on their length, diameter, shape, color and ect. parameters increase market values, decrease product losses and prolong the shelf lifes since damaged ones were separated. In this way, agricultural products are put into certain standards. Thus the resultant product will have a price and sale superiority.

Development, implementation and training of image processing techniques are only possible with classical programming languages and techniques. There are various image processing software in practice. UTHSCSA Image Tool, Nih Image, Scion Image, ImageJ, Optimas, Win/MacCAM, MATLAB, PC Image, Mac and Windows Lispix and VayTek Image are among the significant ones. These software are designed for various purposes. Therefore, functional libraries for image processing algorithms have been added to programming languages and they have made ready-to-use tools, even special software have been developed for such purposes (Gonzalez and Woods, 2008).

Ostrozlik (1990) classified Nantes, Olympia and Schantenay carrots manually and with a classification machine and compared the classification results. The researcher concluded that computer-aided classification required less labor than manual or machine classification.

Feng and Qixin (2004) carried out a study on a single-line prototype fruit classification system and classified Crystal Fuji apples based on color characteristics. The researchers calculated color ratios apples with HSI color space and indicated that fruits could be classified with a success of 90% in this system.

Vursavuş and Özgüven (2008) carried out study to estimate mass of oranges through image processing technique and indicated that mass of oranges could be measured by using image processing technique and different geometric characteristics of oranges. The researchers developed mathematical models by using projection areas, dimensional properties and volumetric characteristics of the oranges and indicated that mass of oranges could be estimated with 85-90% reliability.

Liming and Yanchao (2010) presented the systems to classify strawberries based on their shapes, sizes and color characteristics. The system developed for classification included a belt conveyor, camera, black box (lighting chamber), two photoelectric sensor and electric motor. The system was controlled by a microprocessor (SCM) and a computer. The researchers identified the failure ratio in classification of strawberries based on their sizes as below 5%. The reliability in color-based classification was reported as 88.8% and reliability in shape-based classification was reported as 90%. The process time for a single strawberry was below 3 seconds.

Xiao-bo et al. (2010) used multi-color camera and threshold two-color apple surface. The researchers reached to 96% reliability level in classification of multi-color apples.

Hetal et al. (2012) indicated that on-line rapid, accurate, consistent and realistic quality assessments of horticultural products could be implemented by using image processing techniques. The researchers indicated that machine-vision technology with proper optic and screening systems could yield reliable information about dimensions, shape, color, and surface flaws of horticultural

products. They reported the classification efficiency as 99.24% and quality as 98% and also pointed out that product volume could be calculated by using 3D images.

Sofu et al. (2013) used image processing techniques to determine color, dimension and spots over apple surfaces and to classify the spots. The researchers worked out on 201 apple images and obtained a classification success of 99% in color estimation of apples and 65.52% success in classification of apples based on their types. They worked out on 10 spotted apples and identified 7 spotted apples. They pointed out that image processing was commonly used instead of real-time work out in literature. They had real-time images from continuously moving belt and carried out classification. Processing time of software varied based on the quality of computer used in processing and reported classification time for a single apple as between 1 – 1.5 seconds in a Laptop with an Intel i7 processor.

Clement et al. (2013) classified 360 cucumbers by using ellipsoid and contouring methods They used open code libraries OpenCV 2012 for image processing and developed classification software in C++ programming language. Nokia QT 2021 Library with graphical functions was used for graphic interface. They reported error rate as 15% in classifications with active contour method and as 16% in classifications with ellipsoid approach method.

Zhang et al (2014) noted that, appearance is a very important sensory quality attribute of fruits and vegetables, which can influence not only their market value, consumer's preferences and choice but also their internal quality to some extent. External quality of fruits and vegetables is generally evaluated by considering their color, texture, size, shape, as well as the visual defects. Over the past decades, computer vision systems, including traditional computer vision system, hyperspectral computer vision system, and multispectral computer vision system, have been widely used in the food industry, and proved to be scientific and powerful tools for the automatic external quality inspection of food and agricultural products.

Zhang et al. (2015) presented method to detect defective apple using computer vision. The used Relevance Vector Machine (RVM) as classifier. Average color, statistical, and average textural features were used as inputs. Totally 160 apples used for application. Detection accuracy as 95.63% was obtained.

Jhawar (2016) proposed the study for automated Orange grading. Pattern recognition techniques have been applied on the single color orange image. Four features were used to classifying. 160 orange samples have been used for experiment and have been achieved 90–98% accurate rate.

Donis-Gonzáleza et al (2016) used image processing for carrot classification. CT image preprocessing, cropping, and segmentation, 3762 grayscale intensity and textural features were extracted from the eighteen CT images per sample. A 4-fold cross-validation linear discriminant classifier with a performance accuracy of 87.9% was developed using 95 relevant features, which were selected using a sequential forward selection algorithm with the Fisher discriminant objective function. This objective method is accurate in determining the presence of undesirable fibrous tissue in pre-processed carrots.

Dursun, et al. (2017) In order to determine the percent crop residue cover using ImageJ image processing software and Labview Vision Assistant Module, photographs were taken with a digital camera of the intelligent mobile phone from various places of a field covered with wheat surface residues. İmage processing software ImageJ and Labview Vision Assistant Module were determined as 44.13%, 50.72%, 56.56% and 64.49%, respectively.

Sofu et al. (2016) proposed an automatic system for apple sorting. This system based on real-time processing. The designed system classified three types of apples: Golden Delicious, Granny Smith and Starking Delicious. As feature color, size and weight have been. They used 183 samples for experiment and achieved 73–96% accurate rate.

Moallem et al. (2017) proposed an algorithm for apple grading. They used MLP for segmentation. For classification aim SVM, MLP and KNN have been used. 120 samples used for experiments. They classified apples as healthy and defected. SVM achieved best accuracy rate.

Piedad et al. (2018) developed algorithm for banana classification. Bananas were classified on four classes. As the classification method ANN, SVM and random forest were used. Four features were used to classifying. Random forest achieved higher accuracy as 94.2%.

Carrots are packaged as 1 kg (very rare), 5kg, 10kg by the workers when they are posted on the market. Small, large, damaged, crooked carrots are mixed in these packages. The prototype

machine developed in this study provides automatically classification the carrots according to the features such as height, shape, using image processing technologies. In this study, besides the mechanical and electronic structure of the machine, the logic of working with image processing software is given.

2. Materials and Methods

2.1. Materials

The frame of classification machine operating with real-time image processing technology was formed by aluminum sigma profiles. In classification system, there was a reducer motor driving the belt and a frequency changer able to adjust the speed. A dark chamber (cabin) was designed to prevent shadow formation over the images. Proper apparatus were placed in dark chamber to adjust the distance of light system and cameras from the belt. System control unit was formed with computer and screen connection cables. General view of the machine was presented in Figure 1 and specifications were given in Table 1.

The frame of belt system was composed of 129x23mm conveyor profile and 45x45mm sigma profiles. The dark chamber was made of 45x45mm sigma profiles and connection parts of servo motor and other electronic devices were made of 30x30mm sigma profiles. Corner profiles were connected by using casted connection parts. Aluminum casting sections were used for bearing of belt drum of the system and for installation of driving system. The belts used for agricultural purposes was made of white colored (RAL 9013) polyurethane/polyester coated materials. Belt length was 12.84 m and width was 345 mm.

Figure 1. General view of classification device operating through image processing (Ornek, 2014).

Table 1. General view and specifications of classification device operating through image processing

Length	: 6.51 m
Width	: 0.41 m
Height	: 0.79 m
Dark Chamber Dimensions(L/W/H)	: 0.75 m / 0.44 m / 0.88 m
Operating Width	: 4.20 m
Servo motor installation length	: 4.20 m
Number of servo motors	: 1 - 8 connectable
Number of separator plates	: 1 - 8
Separator plate dimensions (L/W))	: 0.20 m /0.10 m
Number of plastic crates	: 8
Plastic crate dimensions (L/W/H)	: 0.60 m / 0.32 m / 0.40 m

2.1.1. The structure of the subdivisions of the system

a. Belt drive system

The electric motor driving the belt has a power of 0.37kW (Gamak AG71-2a 2800 l/min, 220/380V) and was installed vertically at 90° (Figure. 1). The electric motor was coupled with a reducer (Oztekfen ESV40; 1/50) at 1/50 reduction rate. Belt drum diameter is 12.26 mm. The motion transferred to drum made of polyamide material. An AC frequency changer (ABB ACS150 driver) was installed to control the rotational direction and speed. A frequency range of 0 to 50 Hz was provided with the potentiometer and motor speed was adjusted.

Installation of servo motors and baffle plates were presented in Figure 2a. An installation of the cards into the system was presented in Figure 2b. Ball casters were used to prevent the delay due to friction of the gates to the belt and belt abrasion.

| (a) | (b) |

Figure 2. Installation of baffle gates (a), operation of baffle gates (b) (Ornek, 2014).

b. Encoder and photocell electronic system

An encoder and a wooden wheel were used for loopback information. As an encoder, 500 pulse/rotation, KoyoTrd J500 (Nema17) encoder with 8 mm shaft diameter operating by incremental encodes was used. Incoming signals were converted into RS-232 communication protocol and read to software prepared in the computer through an electrical circuit presented in Figure 3. The 16F877 microcontroller was used over the encoder card. PIC program was written for encoder. Then encoder was installed into belt system and each rotation of the belt was measured as a pulse. A Pepperl Fuchs GLV18 55-73-120 photocell with an operational range of 0.65 m was placed over the conveyor belt to see if there is a carrot within the image taken by the camera. An H85 reflector was installed across the photocell. Photocell and encoder operates over the same card and transfer the information to a computer through a COM port.
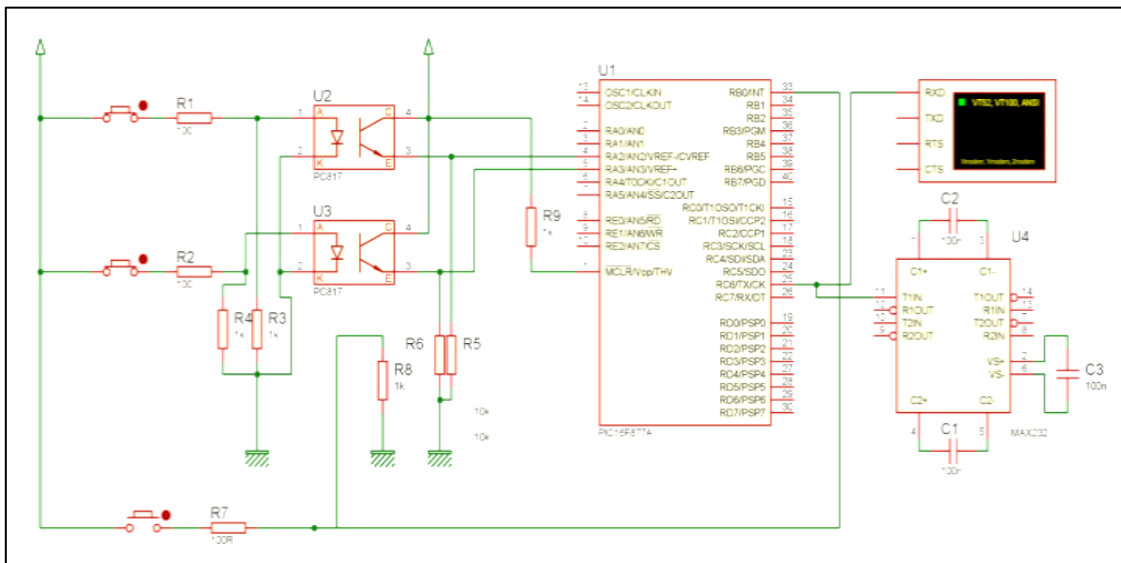

Figure 3. Encoder circuit diagram (Ornek,2014).

c. Servo motors and controls

Servo motors (TowerPro MG995) were used in classification machine operating with image processing to direct the carrots to crates and to move the mobile gates. Servo motors are able to generate 15 kg/cm power at 6V. Delay time was 4 µ seconds. Each servo motor driver card was designed as to drive four servo motors. Number of electronic cards can be increased by adding one another. Card addresses can be arranged through dipswitch over them. With this addressing, the information about the degree of opening-closing can be send with the servo motors connected to the card. This method operates the relevant servo motor with the commands sent.

Electronic diagrams were presented in Figure 4 (a, b, c). The circuit diagram transferring the data coming from servo motor drivers to the computer through RS-485 communication protocol which MAX 487 was used as the communication integrates. 16F877 microcontroller was used in servo motor cards and 5V and 12V direct current feed were supplied to electronic card.
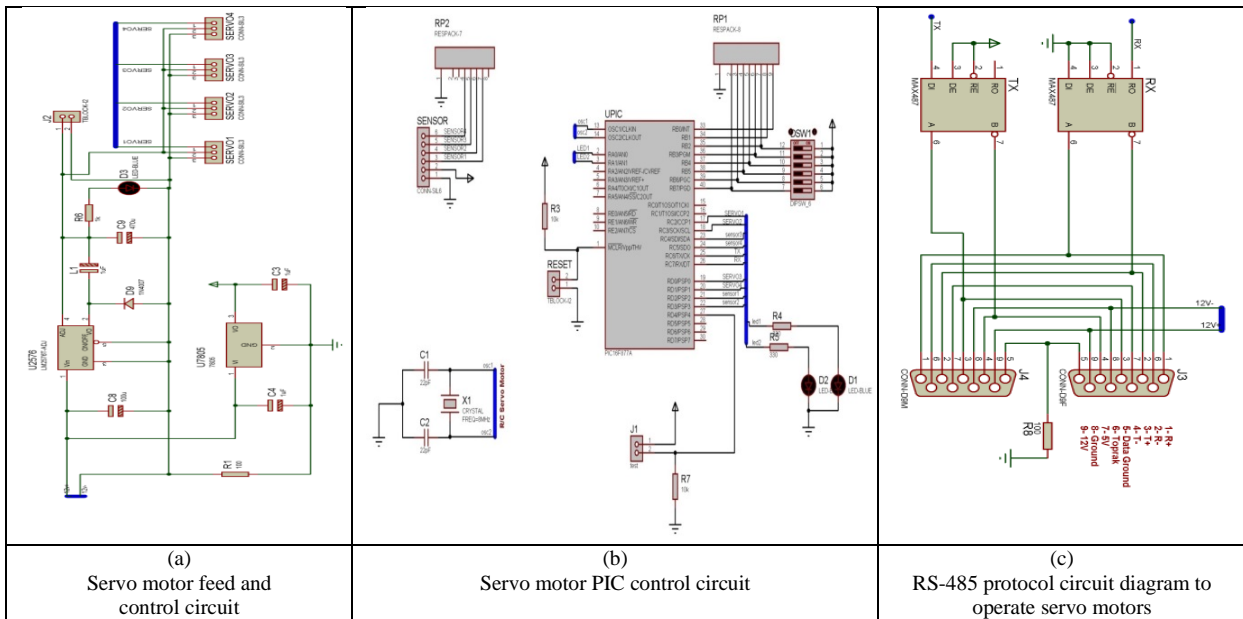

(a)	(b)	(c)
Servo motor feed and control circuit	Servo motor PIC control circuit	RS-485 protocol circuit diagram to operate servo motors

Figure 4. Electronic circuit diagrams (Ornek, 2014).

d. Closed cabin and equipment

In image processing systems, light flashes and shadows over the images constitute the greatest problems. They may create errors in measurements in grey conversion. Light sources and camera system were operated in a cabin to minimize shadow formation. Lighting system was installed for clearer image formation. Ground glass was placed in front of light source to minimize shadow formation of the light distribution over the base (Figure 5).

Figure 5. Cabin lighting, ground glass and camera system (Ornek, 2014).

Led lighting system providing white lamination was placed into the cabin. Led lighting system was placed in a linear order. Led lights were feed with 12V direct current. In lighting system, the 12V-fed LEDs with IP20 protection and 20 000 hours life able to supply 6 000 K Color temperature were used.

e. Camera systems

In image processing system, 1280x1024 pixel Ueye UI-3240CP-M camera with 10bit color depth, E2V sensor and 60 fps value able to be connected to a computer through USB 3.0 was used. Azure C-Mount, 2MP, 12, 16, 25mm C-mount lens was installed in front of the camera. The camera was placed as to vertically see the belt conveyor and be right in the center of lighting leds.

f. Control computer

The computer used to control image processing and classification machine had specifications of Intel Core i7 3770K, Intel Z75, DDR3 16 GB, AMD Radeon HD7950 2GB graphic card. Two Digitus PCI RS-232 cards were installed to communicate with electronic cards. uEye UI-3240CP-M camera was connected through USB 3.0 port.

2.1.2. Software and libraries

Software for image processing system was written by Microsoft Visual Studio 2012 C++ and C# programming language. Visual Studio 2012 C# was used to assess the data coming from control cards of servo motors and encoder. As the image processing software, OpenCV open source code image processing library was used. OpenCV library is based on real-time implementations in image processing and written with optimize C and designed for multi-core processors. The basic purpose of OpenCV is to provide library architecture to create advanced image processing practices in relatively rapid and easy fashion. Video reading processes are formed with the functions in OpenCV 2.4.8 library (Bradski, 2008).

Real-time image processing program was composed of two screens. Operational values of the machine, camera and encoder values, diameter and curvature input values to arrange the communication portal are placed in one screen and video display section is placed in the other screen. In video display screen, camera images, process steps and measured carrot values are displayed (Figure 6).

Display of settings screen of carrot program (image processing program) in the 1st section of video display, one button is used to activate the camera. Encoder pulse settings are located in the 2nd section of settings screen. In this section, the carrot separation crate at pulse value from the place where camera is mounted is defined. Relevant servo motors are driven when the pulse values are realized and carrot is then directed to relevant crate. The duration of gate opening is also adjusted from this section. For registration of the image and image steps, an initial value is assigned to images. In the 3rd section of settings screen, length and diameter ranges are defined. Minimum and maximum values are entered as not to have overlapping values. Screen displays of the program setups are presented in Figure 7.

Video display of image processing program screen in the 1st section of video display, one button is used to activate the camera. Live-image is monitored in a separate display and used to process the previously recorded images. In this display, number of processed carrots and encoder instant values can be seen. The belt movement can also be monitored from this display. One button is used to clear out the initial positions of servo motors, encoder number, image folders and data base. One button is used to process the images of a folder.
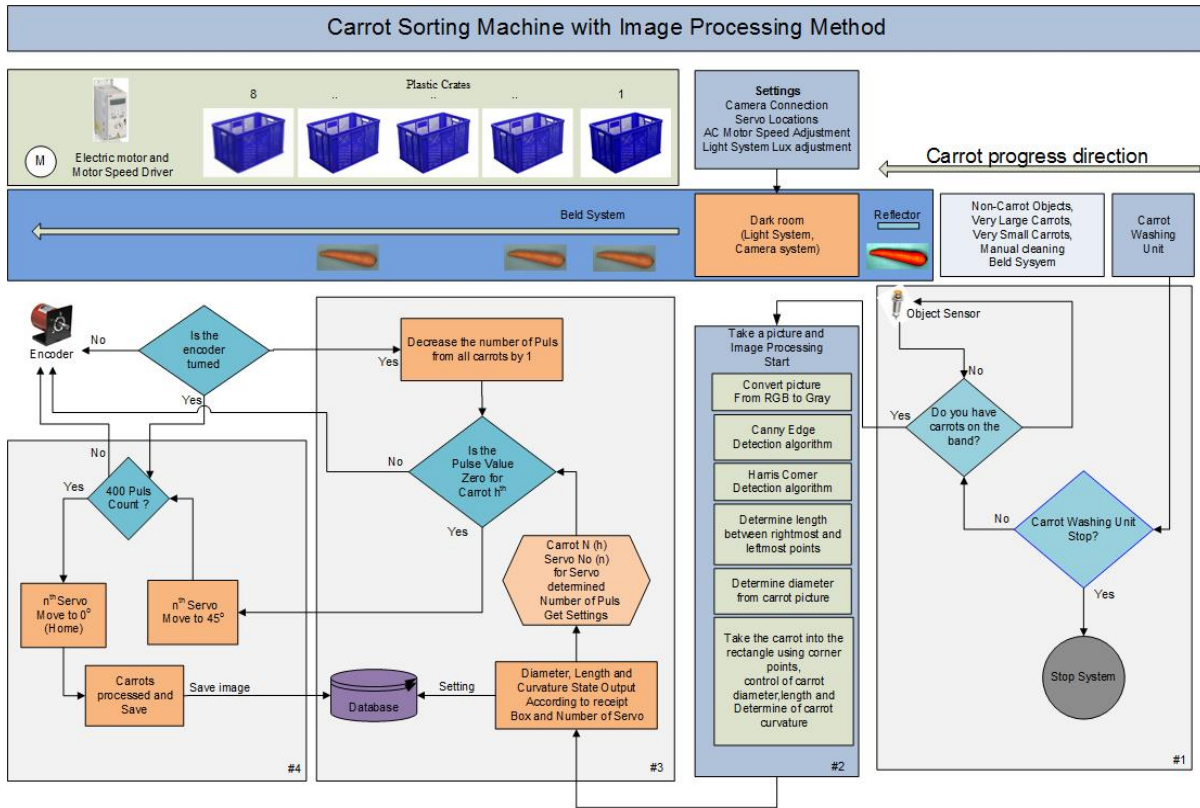
Figure 6. Carrot Sorting Machine Algorithm (Ornek, 2014).

Before operation of carrot classification machine operating with image processing method, the diameter values to be collected in each crate were identified based on the maximum and minimum values in settings section of the program.
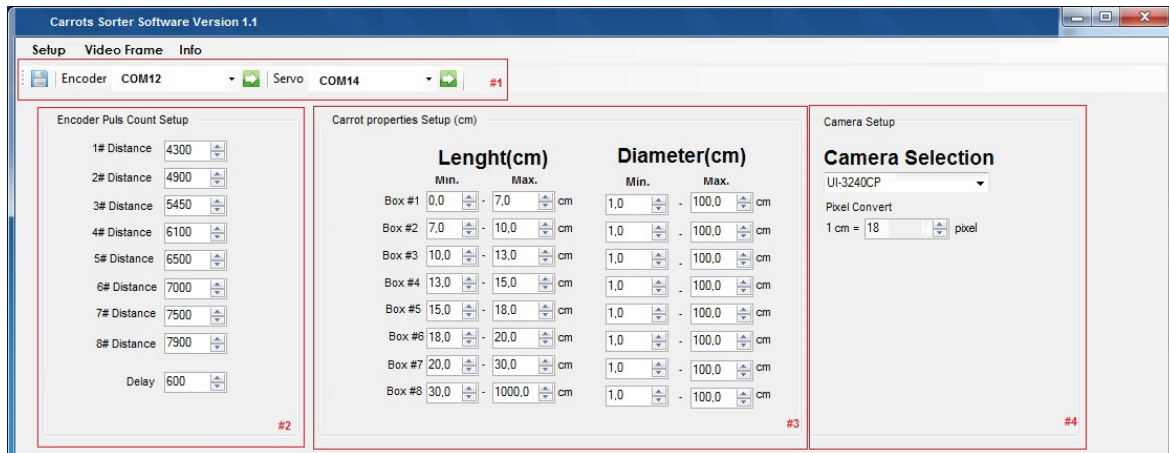

Figure 7. Displays of setting screens of carrot program (Ornek, 2014).

There may be more than more cameras installed to system in the 4th section of settings screen. Selection of relevant camera is made from this combo-box. Since length and diameter measurements may change based on camera installation place and distance from the belt conveyor, the partition ratio is entered based on camera location. In other words, the pixel value for 1 cm is defined. Screen displays of the program setups are presented in Figure 8.
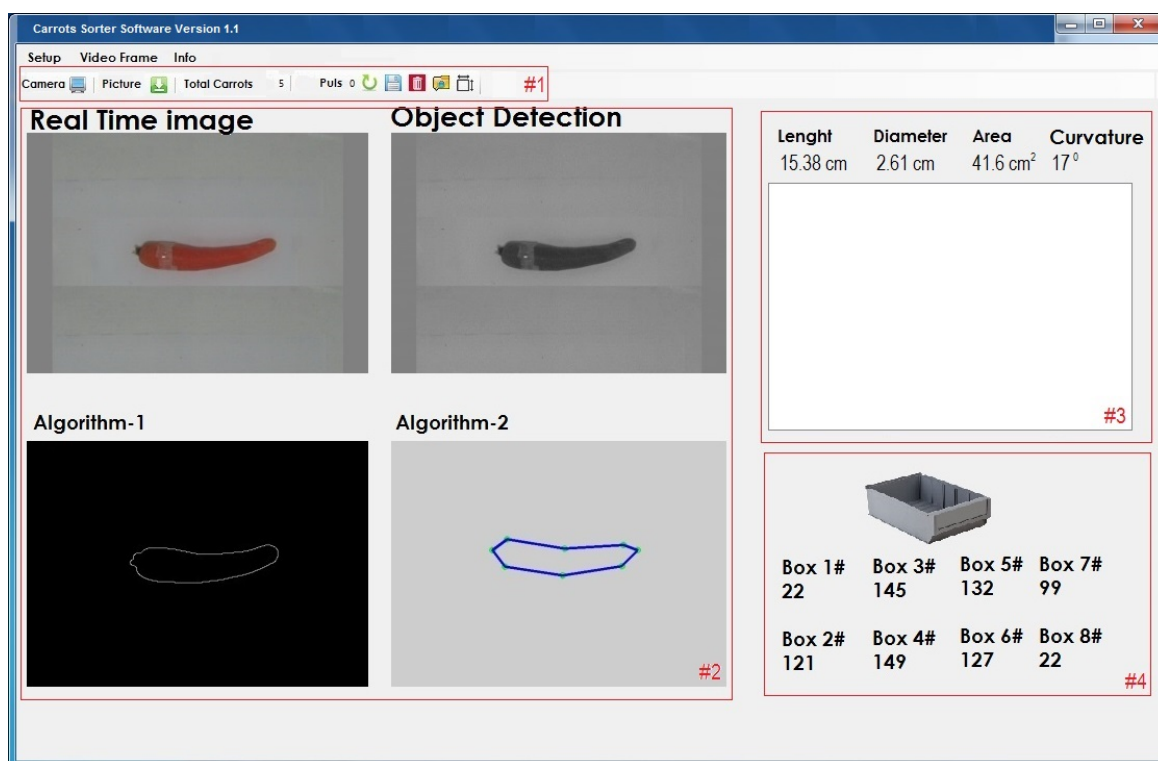
Figure 8. Image processing of carrot program (Ornek, 2014).

2.2. Method

To catch an image from the video display, the photocell creates an image when the carrot passed between photocell and reflector. The information of this value and encoder ration value were combined together and sent through serial port. When the carrot got between photocell and reflector, photocell sends one bit as a value. With each rotation, the belt sends one bit as a pulse.

The 3 matrix value in color images will be converted into single matrix value grey tones and the range 0-255 covers 256 grey tones. In this way, size of images to be processed is decreased and processing time is shortened.

Thresholding process is performed since it is hard to distinguish the items from the base information in grey images. Therefore, base information should be distinguished from the item information. Thus, base pixel values should be set to zero. Some of the pixel values of an image can be set to zero and the rest is obtained by one conversion. Reverse of this process can also be applied. Such a process is called as thresholding (Gonzalez and Woods, 2008).

Canny Edge Detection is the most common algorithm to identify the edges of items. It is composed of a multi-stage algorithm developed by F. Canny in 1986 (Bradski, Kaehler, 2008).

Harris Corner Detection is an algorithm developed to identify the tips of items. This algorithm was developed by Chris Harris & Mike Stephens in 1988 (Bradski, Kaehler, 2008).

Received image, grey image, the images created with algorithm-1(Canny contouring and Gauseen methods) and algorithm-2(Harris Corner Detection) and the angle of the carrot from horizontal plane are displayed in the 2nd section of video display screen In carrot length determination process, initially the horizontal distance between the tips of carrot was determined in pixels.

The diameter was determined in pixels from the largest section by scanning the carrot image over horizontal plane. These values were then divided by scale value to get actual mm value for curvature value; two points vertically intersecting carrot side lines within 10% right and left of carrot total length were identified. These points are then connected to the largest or the narrowest side points. The average of angles formed between these lines is taken as curvature angle. Pre-treatments revealed that this value should be limited with 15° (Figure 9).
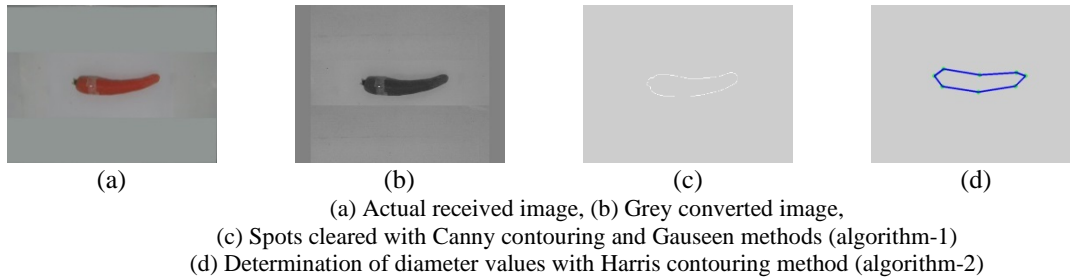
(a)   (b)   (c)   (d)

(a) Actual received image, (b) Grey converted image,
(c) Spots cleared with Canny contouring and Gauseen methods (algorithm-1)
(d) Determination of diameter values with Harris contouring method (algorithm-2)

Figure 9. Image displays of process steps of carrot program (Ornek, 2014).

Program process steps are as follows:

a. With the information coming from photocell and encoder, the information as "there is a carrot (126-63)" and "there aren't any carrots (127-0)" is monitored from the control unit.
b. The information of "there is a carrot" creates an interrupt request.
c. The camera interface having the interrupt request receives an image from the camera and convert the image into grey image in jpg format and return it.
d. The image is converted into grey, then into thresholding value and sent to edge detection algorithm.
e. Corner detection algorithm is used to get curvature and diameter information.
f. Within specified diameter ranges, relevant servo motor and encoder number are created.
g. These information is sent to servo motor control unit through the software developed.
*h.*The relevant servo motor is driven for the carrot with equalized encoder number and gate is opened.
i. Carrots are directed to crates with belt conveyor movement and opening of servo motor gates.
*j.*All these processes are repeated for each carrot.

Randomly selected carrots representing each diameter group and curvature were used to test real-time operation. Diameter, length and weight of these carrots were measured. Then they were placed over belt conveyor manually and real-time images were taken and assessed during belt movement and carrots were directed to relevant crates.

3. Results and Recommendations

Diameter ranges of real-time image processing machine can be arranged as desired. Therefore, it is possible to classify the carrots proper to desired carrot class. A series of pre-tests were performed. These pre-tests revealed positive outcomes for lighting sources only with led light sources. The shadows formed while the flowing image processing created another problem. Camera settings were changed to overcome these problems. Brightness, contrast and color intensity values of the camera were changed and the images with less shadow were obtained. The stains and lines formed over belt conveyor was tried to be eliminated with program filtering algorithms.

Large packing facilities with 35-40 workers are able to pack manually up to 50 tons in a day carrot. Due to fast belt conveyor from the cleaning pool, mechanical classifiers are able to classify as small and big about 5 tons in an hour. Carrot prices may increase through diameter-based classification. Such a case may then provide more value-added to agricultural production facilities.

Our software can process an image with a minimum processing time of 458ms and a maximum of 822ms. Due to the delays in mechanical systems (belt, baffle plates etc.) and electronic systems (Rs-232, communication etc.), there are delays in processes. The time that a carrot stays on the band varies depending on the band speed. The average time to stay on the band is about 2.8 and 12.2 seconds on the first and last baffle plates, respectively. Hourly capacity of developed real-time image processing classification machine is about 350 kg per belt. Parallel belts can be used to reach the desired facility capacity. As a result of the experiments, carrot classification rates ranged from 80.14 to 100% in real-time image processing machine.

Following recommendations can be made based on the experimental results of this study:

* Carrots should be subjected to pre-treatments in real-time image processing classification machine. Large, small carrots or foreign objects should be removed.
* Feeding arrangement should be designed for real-time image processing classification machine.
* Further studies should be carried out with faster belt movements and real-time cameras of real-time image processing classification machine.
* Real-time image processing classification machine can be used in parallel lines to have desired capacities of packing facilities.
* Some sections of program algorithm may be removed and processing time for each carrot can be reduced below 258 ms.
* Color of belt conveyor and light source should be so selected as to prevent shadows.
* Further experiments should be carried out to reduce the shadows formed at extra diameter class.
* Gate sizes may be reduced and thus lower power servo motors can be selected and failure of electronic circuits can be reduced.
* Image processing machine can be integrated to packing machines for future purposes. In this way, a kilogram packs can be made.
* Image processing system can be adapted for classification of other agricultural products. It may be used in classification of cucumber, zucchini, bell pepper-like vegetables.

Acknowledgment

References

Anonymous. 2017). http://faostat.fao.org/site/567/DesktopDefault.aspx [Last Accessed:02.02.2017]

Anonymous. (2019). https://biruni.tuik.gov.tr/medas/?kn=104&locale=tr [Last Accessed:14.01.2019]

Bradski, G., & Kaehler, A. (2008). *Learning OpenCV, Repkover*, United States of America, ISBN: 978-0-596-51613-0.

Clement, J., Novas, N. J., Gazquez, A., & Manzano-Agugliaro, F. (2013). An active contour computer algorithm for the classification of cucumbers, *Computers and Electronics in Agriculture, 92,* 75–81.

Donis-Gonzáleza I.R., Guyera D.E, & Pease A. (2016). Postharvest noninvasive assessment of undesirable fibrous tissue in fresh processing carrots using computer tomography images, *Journal of Food Engineering, 190,* 154-166.

Dursun, İ , Dursun, E , Beyaz, A . (2017). Bitki Yüzey Artığı Kaplama Yüzdesinin Belirlenmesinde Kullanılan Farklı Yöntemlerin Karşılaştırılması. *Yüzüncü Yıl Üniversitesi Tarım Bilimleri Dergisi* , 27 (4) , 550-557 . DOI: 10.29133/yyutbd.297249

Feng, G., & Qixin, C., (2004). Study on Color Image Processing Based Intelligent Fruit Sorting System, *Proceedings of the 5th World Congress on Intelligent Control and Automation*, 6, 4802-4805, China

Gonzalez, R. C., & Woods, R. E. (2008). *Digital Image Processing*, Pearson International Edition, Pearson Prentice Hall, United States of America, ISBN: 0-13-168728-x 978-0-13-168728-8.

Hetal, N., Patel, R.K. Jain. (2012). On-Line quality assessment of horticultural products using machine vision, *International Journal Of Scientific & Technology Research Volume 1,* Issue 9, ISSN:2277-8616

Jhawar, J. (2016). Orange sorting by applying pattern recognition on colour ımage, *Procedia Computer Science 78,* 691- 697.

Liming, X., & Yanchao, Z. (2010). Automated strawberry grading system based on image processing, *Computers and Electronics in Agriculture,71*, S32-S39.

Moallem, P., Serajoddin, A., & Pourghassem, H. (2017). Computer vision-based apple grading for golden delicious apples based on surface features, *Information Processing in Agriculture, 4*(1),33-40.

Ostrozlik, M. (1990). Analysis Carrot of Belgium Sorting. *Zemedelska-Technika. 36*(5), 277-284

Örnek, M.N., (2014). Havuç Sınıflandırmada Gerçek Zamanlı Görüntü İşleme Makinesi Tasarımı Ve Bazı Mekanik Sınıflandırma Makineleri İle Boylama Etkinliklerinin Karşılaştırılması, *Selçuk Üniversitesi, Fen Bilimleri Enstitüsü*, Tarım Makineleri Anabilim Dalı, Konya

Piedad, E.Jr, Larada, J.I., Pojas, G.J., & Ferrer, L.V.V. (2018). Postharvest classification of banana *(Musa acuminata)* using tier-based machine learning, *Postharvest Biology and Technology, 145,* 93-100.

Sofu, M.M., O. Er, M.C. Kayacan, B. & Cetişli B. (2013). Elmaların görüntü işleme yöntemi ile sınıflandırılması ve leke tespiti, *Gıda Teknolojileri Elektronik Dergisi 8* (1), 12- 25

Sofu, M.M., Er O., Kayacan, M.C., & Cetişli, B. (2016). Design of an automatic apple sorting system using machine vision, *Computers and Electronics in Agriculture, 127,* 395-405.

Vursavuş, K.K., Özgüven, F., (2008). Modeling the mass of oranges by geometrical properties, *10th International Congress on Mechanization and Energy in Agriculture*, 14-17 October, 745-751, Antalya

Xiao-bo, Z., Jie-wen, Z., Yanxiao, L., & Holmes, M. (2010). In-line detection of apple defects using three color cameras system, *Computers and Electronics in Agriculture, 70,* 129-134.

Zhang, B., Huanga,W., Lia,J., Zhaoa,C., Fana,S., Wua, J., Liub,C. (2014). Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review, *Food Research International, 62,* 326–343.

Zhang, B., Huang, W., Gong, L., Li J., Zhao, C., Liu, C., & Huang, D. (2015). Computer vision detection of defective apples using automatic lightness correction and weighted RVM classifier, *Journal of Food Engineering, Vol. 146*, 143-151.