Multimed Tools Appl (2019) 78:1613–1634
https://doi.org/10.1007/s11042-018-6271-3

Volumetric estimation using 3D reconstruction method for grading of fruits

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Received: 2 May 2017 / Revised: 7 May 2018 / Accepted: 15 June 2018 /
Published online: 28 June 2018

Abstract Grading of the fruits is one of the important post harvest tasks that the fruit processing agro-industries do. Although the internal quality of the fruit is important, the external quality of the fruit influences the consumers and the market price significantly. External quality of the fruit is based on the features such as color, maturity, shape, texture and size of the fruit. Apart from being expensive and time consuming, the manual grading process may face challenges such as subjectivity in grading, inconsistency and non-availability of the experts during peak seasons. On the other hand, computer vision based fruit grading systems using 2D techniques do not consider self occluding surface of the fruit and fail to determine the percentage of the matured region accurately. The grading systems which approximate the shape of the fruit to a known geometrical shape fail to compute the volume of the fruits with arbitrary shapes accurately. This paper presents a nondestructive and accurate fruit grading system based on the volume and maturity feature implemented using Fuzzy Rule Based Classifier (FRBC). The system estimates the volume of the fruit using volumetric 3D reconstruction method in multiple-camera environment and computes the percentage of the matured region of the fruit with high accuracy. The experimental results show that the accuracy of the proposed grading system in volume estimation and fruit grading is 98.5%. The ability of the proposed 3D reconstruction method to reconstruct the fruits with arbitrary shapes makes the grading system more robust and dynamic.

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Keywords Volumetric reconstruction · Silhouette · Camera calibration · Fuzzy rule based classification · Fruit maturity

1 Introduction

Grading of the fruits is one of the most important post harvest tasks that the fruit processing agro-industries do. The increased classiness and overall awareness of the consumers demand good quality fruits. Although the internal quality of the fruit is important, the external quality of the fruit influences the consumers and the market price significantly. External quality of the fruit is determined on the basis of the features such as color, maturity, shape, texture and size of the fruit. Conventionally, agro industries employ expert labors for grading and separating the fruits based on their quality. Apart from being expensive and time consuming, the manual grading process may face challenges such as subjectivity in grading, inconsistency due to development of the fatigue and non-availability of the expert man power during the peak seasons [41].

With the availability of low cost and good quality consumer cameras, manual and mechanical grading systems are replaced by the computer vision based fruit grading systems [26]. These grading systems mainly focus on determination of features such as size and color of the fruit. These methods offer many advantages such as accuracy, speed, uniformity and consistency in the grading. However, the exiting approaches have some issues which are discussed in the next section.

Since the size of the fruit is directly related to its volume, the volume can serve as an important descriptor for grading and sorting the fruits [28]. Computation of the fruit size is important for numerous reasons. This helps to sort the fruits into different classes as per the size and assign the appropriate price to them. While transporting the fruits, use of volume based packaging optimizes the space occupied in the container. Computation of the volume is also important in density based fruit sorting [28]. 3D reconstruction is a vital component of various computer vision applications. Few significant applications of this field are industrial measurements, surface analysis, volumetric analysis, archeological forensics applications, low dose computerized tomography and robust image reconstruction based on Bayesian priors [6, 8, 18, 39].

This paper aims at the development of nondestructive and accurate fruit grading system using volume and color based maturity feature of the fruit. The system uses volumetric 3D reconstruction method in multiple-camera environment to estimate the volume of the fruit with high accuracy. The grading system employs fuzzy based classification technique for grading the fruits. The ability of the proposed 3D reconstruction method to reconstruct the fruits with arbitrary shapes makes the grading system more robust and dynamic. Moreover, the proposed system computes the percentage of the matured region of entire surface of the fruit using multiple images. This improves the accuracy of the grading system significantly. The experimental results show that the accuracy of the proposed grading system in volume estimation and fruit grading is 98.5%.

The paper is organized as follows. Section two presents the background and motivation for the proposed fruit grading system. Section three throws a light on the proposed fruit grading system using volume and color based maturity feature. The experimental results are discussed in detail in section four. The advantages and limitations of the proposed fruit grading system are also discussed in this section. Section five presents the conclusion.

2 Background and motivation

2.1 Overview

Rapid growth in the field of computer vision and availability of low cost-high resolution digital cameras accelerated the use of vision based systems in many interdisciplinary applications such as fruit inspection and grading. Literature reveals that many researchers have contributed in the development of vision based fruit grading and sorting applications. External quality of the fruit is determined on the basis of the features such as color, maturity, shape and size of the fruit. The fruit grading methods employing computer vision are largely based on 2D techniques, 3D techniques, techniques using different color spaces and techniques using artificial intelligence (AI). In the following subsection, a detailed discussion is made on different fruit grading methods developed by the researchers.

2.2 State of the art

Literature reveals that the earlier research work was focused on 2D techniques where shape and size of the fruit are determined approximately using some interpolation technique. The fruits such as apples, oranges are symmetric about their axis. It is possible to extract their volume using cubic spline interpolation technique. The technique is used to obtain piecewise continuous polynomial of the fruit boundary and its volume [14, 33]. In another approach based on the digital pattern recognition, the algorithm determines key features such as color and boundary from the image of the apple and uses mesh fitting technique to obtain its size [31]. Although the method works well for the fruits with symmetrical shapes, it faces challenges in grading of fruits with arbitrary shapes such as mangoes, strawberries etc. The 2D technique that fits the spline curves to the boundary of mango uses a single image of the fruit. The method employs structural model for analyzing the shape and size of the fruit. Although the method is capable of determining volume of arbitrary shaped fruit, the need of peeling the fruit makes this technique computationally more complex [40].

The methods based on 3D technique essentially compute the volume of the fruit to determine its shape and size. This includes active reconstruction methods based on Time of Flight (ToF) technique and passive reconstruction methods based on volumetric reconstruction technique. ToF method using infrared laser range finder computes the 3D shape of the fruit and uses it as a feature for the fruit grading. ToF based methods are accurate in estimation of the volume [15, 17]. Fruit grading system employing iterative estimation approach computes the 3D shape of the kiwi fruit using laser triangulation technique. The method combines image based parameters with laser triangulation technique to reconstruct the surface of the fruit for determining its volume. However, accuracy in the volume estimation depends on the resolution of the laser scanner [36].

Some volumetric methods use a single camera to reconstruct the volume of the fruit whereas some methods use passive stereo for the same purpose. The techniques using a single camera determine the shape of the fruit by approximating its shape to known geometrical shapes. The curve like structures for 3D reconstruction can be extracted even with the user specific point if backtracking is employed along with the minimal path propagation [21, 34, 37]. The methods employing dense stereo matching compute the point feature correspondences from multiple images and compute the 3D shape of the object. However, stereo reconstruction of the object like fruit which have very few surface features is a challenging task. Use of semantic shape priors can overcome this issue. Volume can also be estimated using orthographic silhouettes rather than conical projections in case of small sized fruits such as strawberries [3, 13].

Literature reveals that the researchers have used different color spaces and segmentation techniques for extracting the Region of Interest (ROI) and determination of the maturity of the fruit. Many techniques for maturity prediction of fruits make use of RGB color space to extract main color features and derived features further to predict the maturity and classify the fruits using SVM classifier. Some methods make use of direct color mapping for determination of the maturity of the fruit whereas some methods use fusion of different features such as color, shape and size and employ SVM for fruit grading [22, 29, 32]. On the other hand, a number of fruit grading methods use different color spaces such as CIE L*a*b and HSV color space instead of RGB color space. The advantage of HSV color space is its consistency with the Human Visual System (HVS). This also helps in accurate segmentation of the fruit from its background [10, 20]. The fruit grading systems based on the color features need to segment the fruit from its background as an essential preprocessing step. Segmentation of the object becomes challenging under the changing light conditions. The segmentation process can be made adaptive to the light conditions by using automatic light adjustment system. The methods use Otsu's thresholding technique for this purpose [19, 27]. Other than SVM, researchers have used Artificial Neural Network (ANN), Rule Based System (fuzzy classifier) and K Nearest Neighbor classifier (KNN) as an AI tool for the fruit grading applications. Fuzzy logic based classifiers are preferred over SVM classifiers for maturity prediction and classification of the fruits. The advantage of the fuzzy logic is its straightforwardness and simplicity. The presence of random-valued impulse noise in the system may be vital in fruit grading applications. An iterative structure-adaptive fuzzy estimation technique can help in estimating such noise further to remove it efficiently [11, 24, 38].

2.3 Issues and motivation

Volume and maturity of the fruit are important descriptors for their grading. 3D reconstruction techniques compute the volume of the fruit more accurately than their 2D counterparts. The grading systems employing 3D techniques which approximate the shape of the fruit to the known geometrical shapes fail to compute the volume of the fruits with arbitrary shapes accurately whereas 3D reconstruction methods using stereo approach face challenges while reconstructing the fruit objects since they have very few surface features. This degrades the accuracy of the grading system further. Most of the computer vision based fruit grading systems employing 2D techniques use a single image of the fruit to determine the maturity of the fruit. These systems do not consider the self occluding surface of the fruit and fail to determine the percentage of the matured region accurately. These limitations serve as the motivation for the proposed work.

This paper presents a nondestructive and accurate fruit grading system based on volume and color based maturity feature of the fruit. Accurate volume estimation done by the proposed volumetric 3D reconstruction method is a major contributing factor in the improved performance of the grading system. The proposed 3D reconstruction method integrates homography estimation and voxel mapping for achieving the greater accuracy in volume estimation. Moreover, the system reconstructs the fruits of arbitrary shapes like strawberries and estimates their volume with high accuracy. Since HSV color space is more HVS consistent, the proposed system determines maturity of the fruit by extracting its ROI in HSV color space rather than RGB color space.

ANN based approaches are computationally complex since they need to train more number of samples for achieving good classification accuracy. Rule based classifiers such as fuzzy classifier is an intuitive classifier which is very robust against changing environments. In addition to that, the classifier is memory efficient too. As compared to SVM, fuzzy classifier is more straightforward and simpler. This motivated the authors to use volume and maturity based Fuzzy Rule Based classifier (FRBC) for grading the fruits. The proposed system determines the maturity of the fruit using multiple images rather than a single image used in most of the 2D techniques. This makes the proposed system more robust and accurate.

3 Methodology

The fruit grading system presented in this paper reconstructs a 3D model of the fruit using the proposed volumetric 3D reconstruction method and estimates the volume of the fruit with very high accuracy. The volume feature is used along with the maturity feature to grade and sort the fruits.

The flow diagram of the proposed fruit grading system is given in Fig. 1. After acquiring multiple images of the fruit using multiple-camera setup, the proposed 3D reconstruction method reconstructs the volumetric 3D model of the fruit and computes its volume in real world units. The flow diagram of the proposed volumetric reconstruction system and the details about each step are presented in section 3.2. The images of the fruit are segmented in HSV color space to extract the Region of Interest (ROI). Subsequently, hue corresponding to the fruit color is used to decide whether the fruit is matured or not. Finally, fuzzy based classifier classifies the fruit into different grades based on the volume and the color based maturity feature. The details of the segmentation process, ROI extraction and the design details of Fuzzy Rule Based Classifier (FRBC) are presented in section 3.3.

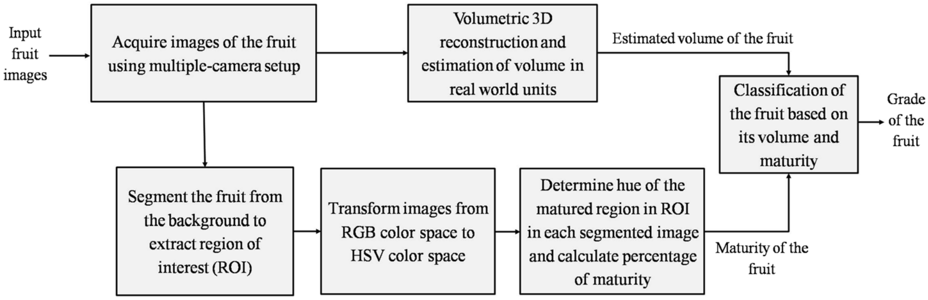

Fig. 1 Flow diagram of the proposed fruit grading system

3.1 Fruit sample collection

The experimentation on the grading system described in the paper is carried out for five different fruits: apple, mango, orange, pomegranate and strawberry with two hundred samples of apple, orange and pomegranate each and fifty samples of mango and strawberry each. While selecting the samples, utmost care is taken to include samples of different size and shapes along with the samples of different maturity levels. The samples are tagged with unique alphanumeric serial number. For example, serial number M1 to M50 are assigned to fifty samples of mango and serial number O1 to O200 are assigned to two hundred samples of orange. Manual grading from the experts is done for these fruit samples to establish the ground truth.

3.2 Volumetric 3D reconstruction of fruits using multiple-camera setup

The flow diagram of the volumetric 3D reconstruction pipeline used to estimate the fruit volume is presented in Fig. 2.

The method uses Nikon-S3600 digital cameras four in number placed at different elevations and a turn table to acquire multiple images of the fruit objects [16]. The size and resolution of all the images is 1600 × 1200 that is, 1.92MP and 300 dpi respectively. The illumination is maintained constant during the image acquisition. Initially the images of the calibration pattern are acquired and used further to calibrate the cameras.

In the next step, limits for the initial volume are determined using camera parameters. Camera calibration is a process of computing internal and external parameters of camera. The Internal parameters of the camera include its focal length, principal point, skew and lens distortion parameters. The external parameters, translation vector and rotation matrix determine the pose of the camera. The camera parameters are used for determining the limits of initial volume and to compute camera projection matrices. The camera calibration tool box developed by Bouguet is used for performing camera calibration of all the cameras [5, 35]. The checkerboard calibration pattern of size 270 mm × 210 mm with each square of size 25 mm × 25 mm is used for the camera calibration. Figure 3 shows few images of the calibration pattern acquired during the experimentation. Accuracy of the camera calibration governs the accuracy of the 3D

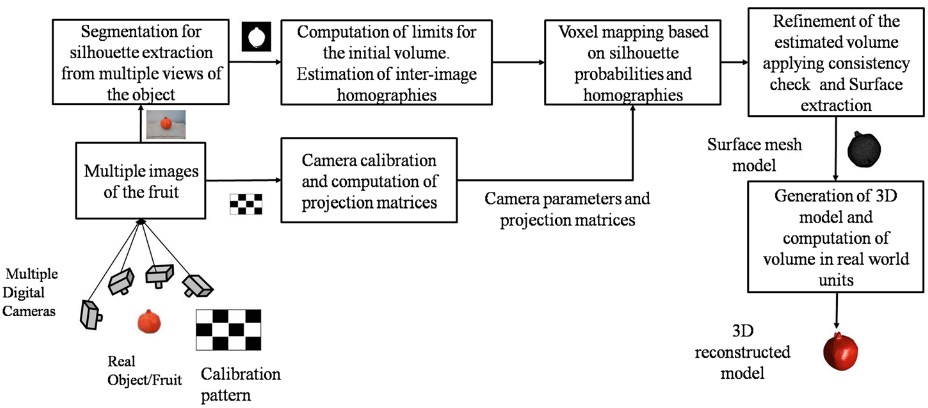

Fig. 2 Flow diagram of the proposed volumetric 3D reconstruction pipeline used to estimate volume of the fruit

Fig. 3 Few images of the calibration pattern used for camera calibration

reconstruction and volume estimation. Hence utmost care is taken while calibrating the cameras.

Later, the images of the fruit are segmented to extract the silhouettes. This information is further used to estimate the silhouette probabilities. Uniform blue background makes the segmentation process simpler and faster. Some non-matured fruits may have color close to the green color. Hence to avoid the complexity in segmentation process, the blue background is preferred over the green background.

In the next step initial volume is discretized to create a voxel space. After computation of silhouette probabilities, inter-image homographies are estimated. Homography is an invertible mapping of the point on one projective plane to the corresponding point on the other projective plane. It is a transform which relates the two image planes. The algorithm uses Direct Linear Transform (DLT) and Singular Value decomposition (SVD) to obtain inter-image homographies [12].

Later, each voxel in the discretized 3D space is projected using the camera matrices on corresponding images. These images are further warped on the reference image to calculate mean squared error between 2D projection in the reference image and 2D projection in the warped images. Inter-image homographies obtained earlier are used for this purpose. Less error signifies the higher correlation between different views of the object. Silhouette probabilities and error estimates are used further to decide voxel occupancies during the voxel mapping process. The voxel mapping process maps the voxels either to the object (foreground) or to the background based on their occupancies. The voxels which are mapped to the background are made transparent. So that only voxels representing the 3D shape and volume of the object are retained. The model is refined further by applying the consistency check.

In the last step, the object surface is reconstructed by extracting isosurfaces. Surface extraction and texture mapping is the final step in the reconstruction pipeline to obtain the final 3D model. The voxel volume obtained from the reconstructed 3D model is converted into real world unit cm^3 by using the camera parameters and voxel resolution. Figure 4 shows step by step results of the proposed volumetric reconstruction method for pyramid shaped object. Figure 4a and b show few images and silhouettes of the triangular pyramid respectively. Figure 4c shows surface mesh model of the pyramid object whereas Fig. 4d shows few views of the 3D reconstructed pyramid using volumetric 3D reconstruction method. The details of the volumetric reconstruction of the fruits are presented in section 4.

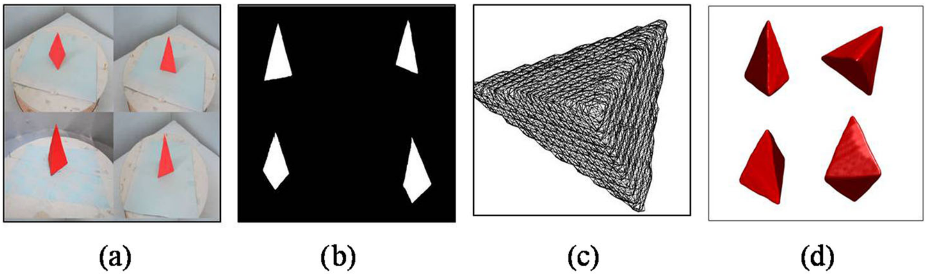

Fig. 4 **a** Few images **b** silhouettes **c** surface mesh and **d** views of 3D reconstructed triangular pyramid object

3.3 Performance evaluation of the proposed volumetric 3D reconstruction method

Performance of the volumetric 3D reconstruction method used for the estimation of the fruit volume is evaluated by reconstructing the objects of known geometry such as cube, sphere, cylinder, prism and pyramid shaped objects. Table 1 presents the estimated volume; the actual volume calculated using mathematical equation and the actual volume of the pyramid object measured using water displacement method. It is observed that the method reconstructs the 3D model of a pyramid with more than 98% accuracy in volume estimation. The method is also tested for volume estimation of nine different toy objects such as duck, bear, red colored fish, puppy etc. which have arbitrary shapes. The average accuracy in the volume estimation is around 98.5%. High accuracy in the volume estimation is a result of accurate camera calibration and voxel mapping technique based on the homography and silhouette probabilities. The volumetric 3D reconstruction methods are computationally less complex as compared to the stereo based methods since they do not need to compute point correspondences. Hence, the method is used in the volumetric estimation of the fruits which serves as an important descriptor for their grading and sorting.

3.4 ROI extraction and design of the fuzzy rule based classifier(FRBC)

Images of the fruit sample are segmented to extract the ROI. The segmentation process uses Otsu's threshold T^* [30] for identification of the foreground and the background. If 'S' denotes the output binary image then,

$$S(x,y) = \begin{cases} 1 & \text{if } g_i(x,y) \geq T^* \\ 0 & \text{if } g_i(x,y) < T^* \end{cases} \quad \text{where } g_i(x,y) \text{ is the pixel value at location } x,y \text{ in } i^{th} \text{ image} \tag{1}$$

Subsequently the fruit color is used to decide whether a fruit is matured or not. HSV color space is more consistent with the human visual system than RGB color space. Also RGB

Table 1 Comparison between the actual volume and the estimated volume of the object with known shape

Object under 3D reconstruction	Actual (real world) volume (cm^3)	Real world volume (cm^3) measured using water displacement method	Volume (cm^3) estimated using proposed 3D reconstruction method
Triangular pyramid with base edge a = 4 cm and height h = 7 cm	$\frac{\sqrt{3}a^2}{12}h = 16.16$	16.40	16.34

colors are device dependent. Hence the segmented images are converted from RGB color space to HSV color space using Eqs. 2 to 4.

$$H = \begin{cases} \cos^{-1}\left(\dfrac{(R-B)+(R-G)}{2\sqrt{(G-B)(R-B)+(R-G)^2}}\right), B \le G \\ 2\pi - \cos^{-1}\left(\dfrac{(R-B)+(R-G)}{2\sqrt{(G-B)(R-B)+(R-G)^2}}\right), B > G \end{cases} \tag{2}$$

$$S = \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} \tag{3}$$

$$V = \frac{\max(R,G,B)}{255} \tag{4}$$

'H' represents Hue, the pure color. 'S' and 'V' represent the saturation and value or intensity respectively. Later, the histogram plots of the hue plane of segmented images are obtained to determine the range of hue for matured and non-matured (raw) fruits. Figure 5 shows an example of a matured orange and a raw orange. It also shows that the hue parameter associated with them has different values. Hue value for a matured (ripened) orange is in the range of 0.05 to 0.09 with the mean value 0.07. Whereas hue value for a non-matured (raw) orange is in the range of 0.1 to 0.18 with the mean value 0.14. Here, the hue values are normalized in the range of 0 to 1. The multiple-camera system acquires multiple images covering the entire surface of the fruit for determining the maturity with more accuracy. This

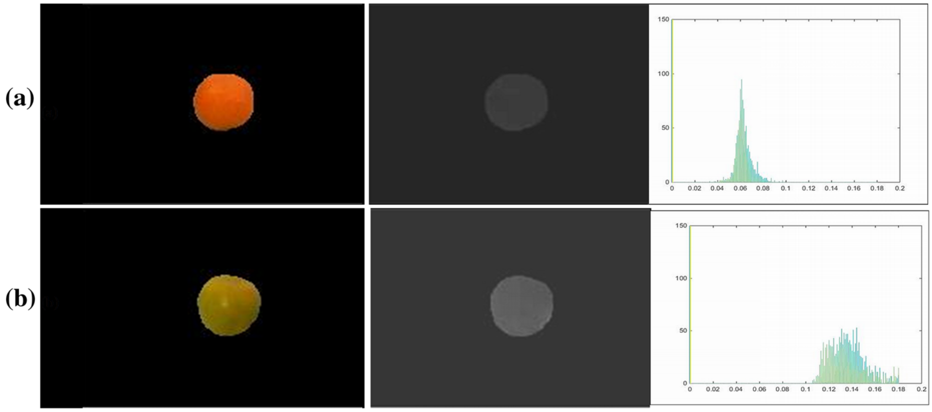

Fig. 5 **a** Segmented view, hue plane of the segmented view and histogram of the hue plane of ripened sample of orange **b** segmented view of a raw sample of orange, its hue plane and histogram showing distinctive range for hue

Table 2 Fuzzy-if-then rules used in the design of the FIS

Volume(cm^3) → Color based maturity↓	A	B	C	D	E
M	G1	G1	G2	G3	G4
R	G3	G3	G3	G5	G5

A: Very big volume, B: big volume, C: medium volume D: small volume E: very small volume, M: Matured, R: raw, G1: very good quality, G2: good quality, G3: medium quality, G4: poor quality G5: very poor quality.

improves the overall accuracy of the grading system. The percentage surface area of the matured region of the fruit is determined using Eq. (5).

$$S_M = \frac{\sum_{i=1}^{N} S_{mi}}{\sum_{i=1}^{N} S_{ti} \times 100} \tag{5}$$

Here, 'S_M' represents the percentage surface area of the matured region of the fruit. 'N' is the number of images/views. 'S_{mi}' is the surface area of the matured region in i^{th} image expressed in terms of the number of pixels with hue value in hue range of the matured fruit in i^{th} image around its mean hue value and 'S_{ti}' is the total surface area of the fruit in i^{th} image expressed in terms of the total number of pixels corresponding to fruit area in i^{th} image.

A fruit is designated as matured, if $S_M \geq 80$. That is, if 80% region of the total surface of the fruit has hue value within the maturity range with corresponding mean value, it is declared as a matured fruit. Else, it is declared as a raw fruit. The threshold value of 80% is decided considering the opinion of three experts in the field. The threshold value is normalized and used for designing the classifier. The samples are categorized into three to five classes by dividing the entire range of volume by referring international guidelines and experts' opinion. For example, apples, oranges and pomegranates are categorized in five classes as class A to class

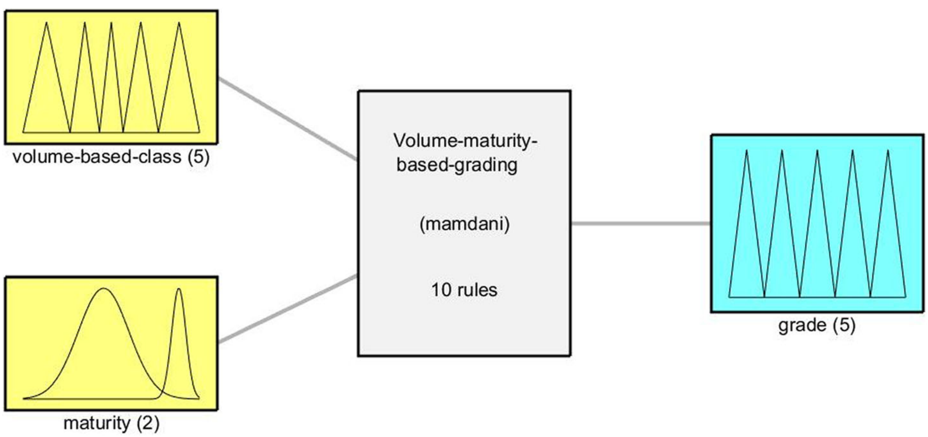

Fig. 6 Fuzzy inference system for grading of oranges

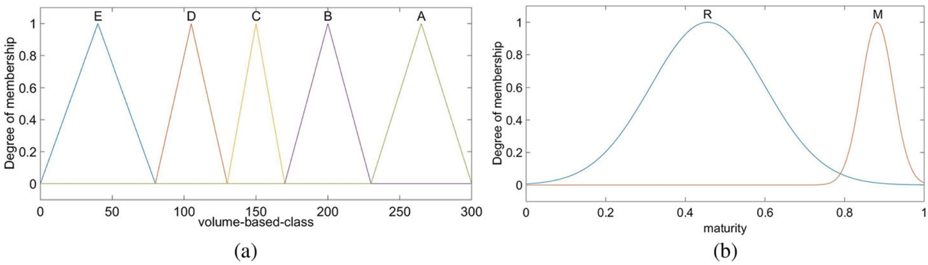

Fig. 7 Input membership functions representing (**a**) volume based class (**b**) maturity of orange

E whereas mangoes are categorized into four classes and strawberries are categorized into three classes. Fuzzy Rule-Based Classification System (FRBCS) is used to grade and sort the fruits. The criteria discussed in above paragraphs are used to partition the feature space into linguistic variables. FRBC system used in the experimentation is based on Mamdani Fuzzy Inference System (FIS) [23]. Table 2 describes fuzzy-if-then rules used in the design of the FIS. Figure 6 shows the fuzzy inference system designed for grading of the samples of orange. Figure 7 shows input membership functions representing the volume based class and the maturity level whereas Fig. 8 shows output member function representing the grades of orange fruits.

As discussed earlier, oranges are categorized into five classes: A ($volume > 230\ cm^3$), B ($170\ cm^3 < volume < 230\ cm^3$), C ($130\ cm^3 \leq volume \leq 170\ cm^3$), D ($80\ cm^3 \leq volume < 130\ cm^3$), E ($volume < 80\ cm^3$) on the basis of volume and two classes: R (raw), M (matured) on the basis of color based maturity. FIS designed for grading of oranges grade the oranges into five categories G1 (very good quality), G2 (good quality), G3 (medium quality), G4 (poor quality) and G5 (very poor quality).

4 Experimental results and discussion

The experimentation is performed on Intel® Core™ i5-2450 M CPU@ 2.50 GHz using windows 7 operating system. The paper presents an excellent application of volumetric 3D reconstruction method using multiple cameras for estimating the volume of the fruit. The experimentation is carried out on two hundred samples of apple, orange and pomegranate each and fifty samples of mangoes and strawberries each. Figure 9 shows the volumetric

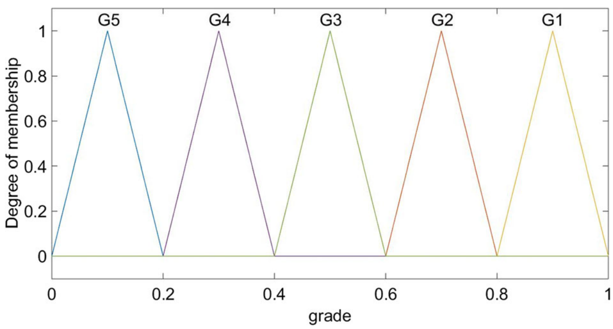

Fig. 8 Output membership function representing the grades of orange fruits

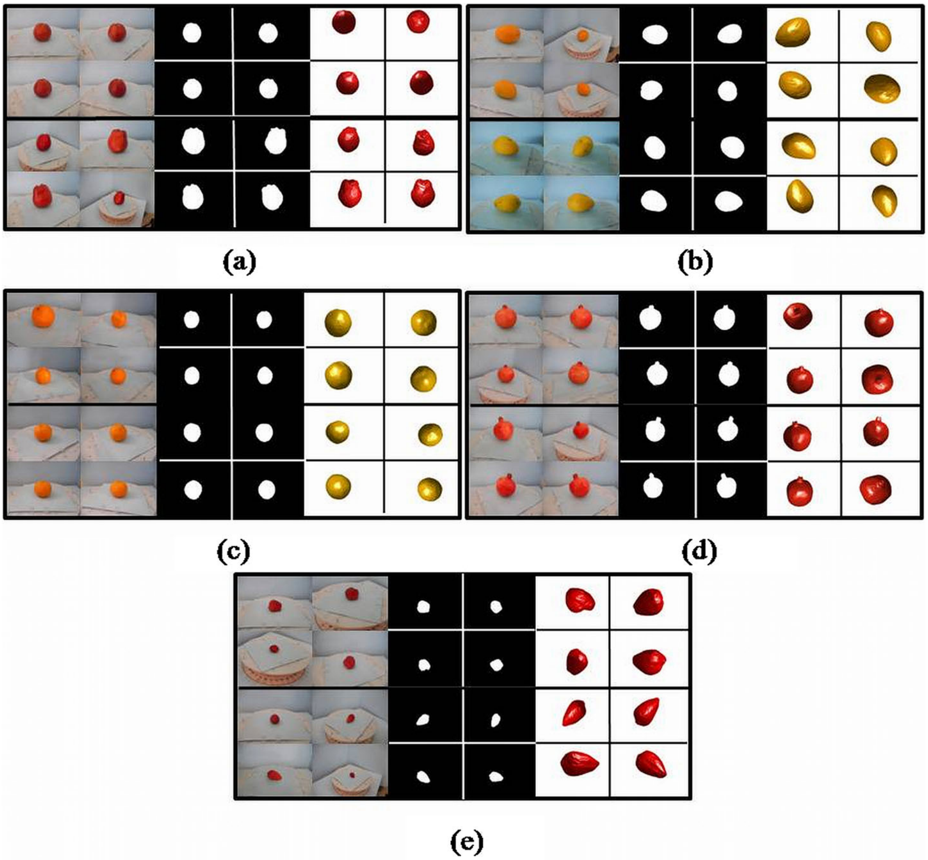

Fig. 9 Volumetric reconstruction of two samples of **a** apple **b** mango **c** orange **d** pomegranate and **e** strawberry

reconstruction of two samples of (a) apple, (b) mango, (c) oranges, (d) pomegranate and (e) strawberry respectively. The figure shows four views of each fruit sample, silhouettes and four views of the 3D reconstruction of each fruit sample with some views from the arbitrary viewpoints. Thus the method is tested for the fruits with symmetrical shapes and the fruits with arbitrary shapes.

It can be clearly seen from the results of the reconstruction that the proposed volumetric 3D reconstruction method using multiple cameras reconstructs the fruits of arbitrary shapes with high accuracy in volume estimation. Stereo vision based methods available in the literature need to find point correspondences between multiple images of the object. Hence these methods are computationally more complex. These methods face many challenges while computing the point correspondences in case of the objects with very few surface features and fail to reconstruct complete 3D model. Most of the natural fruits have uniform surface with very few features. Hence stereo vision based methods may face challenges in 3D reconstruction of the fruits. On the contrary, the proposed volumetric 3D reconstruction method reconstructs the fruit of any arbitrary shape with high accuracy. The volume of the fruit obtained during 3D reconstruction is converted into real world units using voxel resolution and

Table 3 Comparison between volume (cm^3) of hundred samples of orange with serial number O1 to O100 estimated using 3D reconstruction method and their actual volume (cm^3) determined using water displacement method

Sr. No.	Estimated volume (cm^3)	Actual volume (cm^3)	Sr. No.	Estimated volume (cm^3)	Actual volume (cm^3)	Sr. No.	Estimated volume (cm^3)	Actual volume (cm^3)	Sr. No.	Estimated volume (cm^3)	Actual volume (cm^3)
O1	75.37	74.79	O26	137.33	136.77	O51	80.37	79.79	O76	142.33	141.77
O2	64.17	63.45	O27	134.56	133.63	O52	69.17	68.45	O77	139.56	138.63
O3	63.53	62.85	O28	181.21	180.14	O53	68.53	67.85	O78	186.21	185.14
O4	92.07	91.43	O29	160.01	159.18	O54	97.07	96.43	O79	165.01	164.18
O5	87.22	86.85	O30	153.87	152.42	O55	92.22	91.85	O80	158.87	157.42
O6	94.41	93.67	O31	190.49	189.32	O56	99.41	98.67	O81	195.49	194.32
O7	53.32	52.96	O32	145.01	144.34	O57	58.32	57.96	O82	150.01	149.34
O8	67.35	66.85	O33	166.75	165.85	O58	72.35	71.85	O83	171.75	170.85
O9	113.3	112.9	O34	156.67	155.88	O59	118.3	117.9	O84	161.67	160.88
O10	263.06	262.84	O35	178.61	177.8	O60	268.06	267.84	O85	183.61	182.8
O11	173.31	172.75	O36	134.18	133.65	O61	178.31	177.75	O86	139.18	138.65
O12	183.06	182.96	O37	184.14	183.04	O62	188.06	187.96	O87	189.14	188.04
O13	198.08	197.85	O38	183.39	182.3	O63	203.08	202.85	O88	188.39	187.3
O14	227.5	226.9	O39	146.31	145.64	O64	232.5	231.9	O89	151.31	150.64
O15	80.18	79.45	O40	232.44	231.79	O65	85.18	84.45	O90	237.44	236.79
O16	60.38	59.85	O41	134.28	133.75	O66	65.38	64.85	O91	139.28	138.75
O17	73.53	72.9	O42	155.02	154.25	O67	78.53	77.9	O92	160.02	159.25
O18	91.32	90.7	O43	194.82	193.6	O68	96.32	95.7	O93	199.82	198.6
O19	83.75	82.85	O44	298.98	299.39	O69	88.75	87.85	O94	303.98	304.39
O20	57.27	56.72	O45	136.71	136.15	O70	62.27	61.72	O95	141.71	141.15
O21	124.69	123.55	O46	142.28	141.66	O71	129.69	128.55	O96	147.28	146.66
O22	139.27	138.7	O47	270.77	269.68	O72	144.27	143.7	O97	275.77	274.68
O23	146.05	145.38	O48	141.27	140.66	O73	151.05	150.38	O98	146.27	145.66
O24	131.77	130.97	O49	153.61	152.86	O74	136.77	135.97	O99	158.61	157.86
O25	145.79	144.53	O50	150.96	149.74	O75	150.79	149.53	O100	155.96	154.74

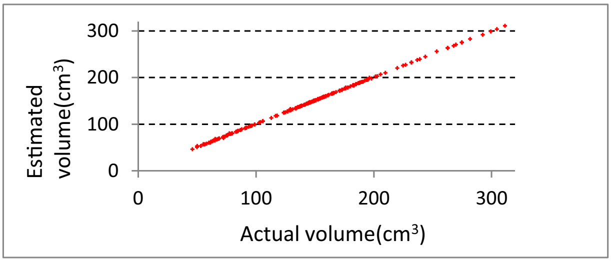

Fig. 10 Scatter plot of the estimated volume and actual volume for two hundred samples of orange

the camera parameters. The estimated volume is further compared with actual volume of the sample obtained using water displacement method.

Table 3 presents the comparison between volume of one hundred samples out of two hundred samples of orange fruit with serial number O1 to O100 estimated using 3D reconstruction method and their actual volume determined using the water displacement method.

From Table 3 it is observed that, the accuracy in volume estimation is greater than 98%. It is also observed that, for a particular fruit, volume of the samples has linear relationship with their weight. This fact helps in mapping weight based grading criteria mentioned in the international guidelines to corresponding volume in order to decide volume thresholds. High accuracy of the volumetric 3D reconstruction method in volume estimation improves the overall accuracy of the grading system. Similar results are obtained for other fruits: apple, mango, pomegranate and strawberry. Since the volume estimation is a major step in the grading system, the performance of the volume estimation is further analyzed using performance parameters- Root Mean Square Error (RMSE) and Root Mean Square Percentage Error (RMSPE) [7]. The equations for these parameters are as follows.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(V_{ai}-V_{ei}\right)^2} \quad and \quad RMSPE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{V_{ai}-V_{ei}}{V_{ai}}\right)^2} \times 100 \tag{6}$$

Figure 10 shows the scatter plot of the volume estimated using the proposed method and the actual volume for two hundred samples of orange. Very small deviation of the estimated volume from the actual volume emphasizes the greater accuracy in volume estimation.

Where, V_{ai} is actual volume of i^{th} sample and V_{ei} is estimated volume of i^{th} sample. N represents the number of samples. Average value of RMSE and RMSPE considering the

Table 4 Defuzzification output and corresponding grades of grading system for oranges

Defuzzification output	Output grade
$grade\ value \geq 0.8$	*very good quality*(G1)
$0.6 \leq grade\ value < 0.8$	*good quality*(G2)
$0.4 \leq grade\ value < 0.6$	*medium quality*(G3)
$0.2 \leq grade\ value < 0.4$	*poor quality*(G4)
$grade\ value < 0.2$	*very poor quality*(G5)

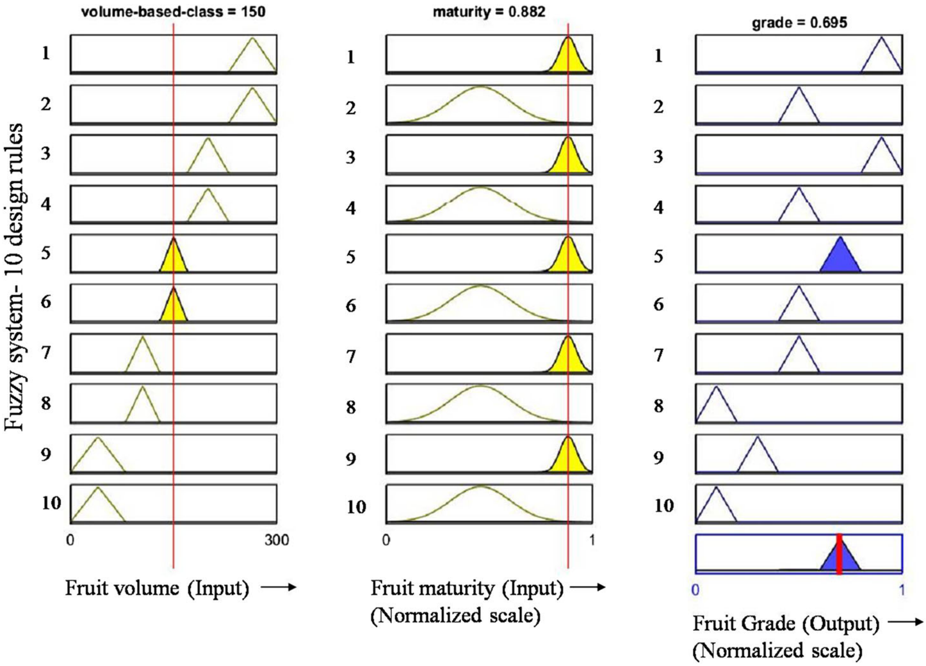

Fig. 11 Defuzzification result obtained from the rule viewer of FIS designed for the grading of oranges

performance of the system for all the fruits is 0.77 cm^3 and 0.8% respectively. Table 4 presents the defuzzification output and corresponding grades.

Figure 11 shows the rule viewer of the FIS designed for the grading of oranges. In Fig. 11, first column of the rule viewer represents the volume of the fruit whereas second column represents the normalized value of the maturity. Based on these inputs the rule viewer generates the normalized value for the corresponding grade as the output. Figure 11 shows that the output value given by the system for sample of orange fruit with volume of 150 cm^3(class C) and maturity 0.882 (88.2%). The output value 0.695 indicates that the sample is graded as good quality (grade G2) fruit.

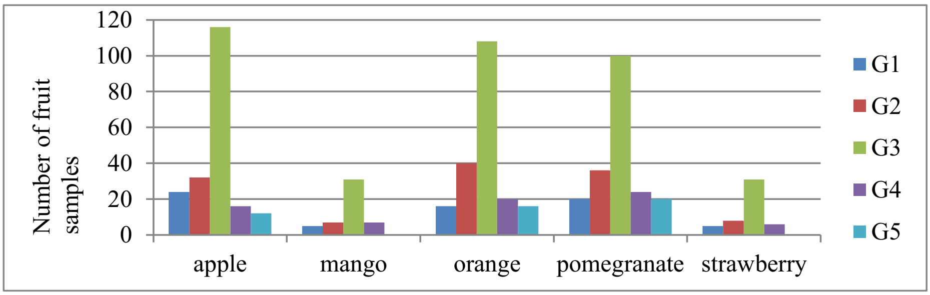

Fig. 12 Results of the grading system based on volume and color based maturity feature for grading of apple, mango, orange, pomegranate and strawberry

Table 5 Comparison between accuracy of classification of grading system using volume and maturity features and average accuracy of classification done by the experts for each grade

Fruit	% accuracy for grade G1		% accuracy for grade G2		% accuracy for grade G3		% accuracy for grade G4		% accuracy for grade G5	
	System	Manual	System	Manual	System	Manual	System	Manual	System	Manual
Apples	99.03	99.40	98.36	99.02	98.49	99.01	98.33	98.81	98.39	98.90
Mango[a]	98.92	99.19	99.02	99.63	98.78	99.09	98.69	99.01		
Orange	98.36	98.63	98.23	98.87	98.33	98.69	98.91	99.36	98.13	98.87
Pomegranate	98.30	98.56	98.37	98.86	98.42	98.86	98.7	98.96	98.49	99.02
Strawberry	98.44	98.79	98.54	99.03	98.69	99.11	99.05	99.51		

[a] mangoes and strawberries are classified into four grades G1, G2, G3 and G4

As discussed in the methodology, mangoes are categorized in four classes, class A, class B, class C and class D whereas strawberries are categorized in three classes, class A, class B and class C. Hence the FIS for grading of the mangoes need eight 'if then rules' and the FIS for the grading of strawberries need six 'if then rules' with four output grades G1, G2, G3 and G4. Figure 12 presents the results of the grading of all the fruits graphically.

Table 5 shows the performance analysis of the grading system for apple, mango, orange, pomegranate and strawberry. The accuracy of classification of FRBC system is compared with the average accuracy of classification performed by the experts for these fruits.

The classification accuracy in the manual grading is high since it is carried out by the experts with utmost care for establishing the ground truth. In practice for grading of huge number of samples, the manual classification may not be accurate. Since it is based on the expertise of the manual graders, it is highly subjective. The manual graders may develop a fatigue due to repeated task. This affects the overall accuracy of the grading process. Hence automatic grading systems having accuracy close to the ground truth are needed. Results of the classification show that the system classifies the fruits of symmetrical and arbitrary shapes with high accuracy. Accurate volume estimation done by the volumetric 3D reconstruction method using multiple cameras discussed in the paper is a major contributing factor in the improved

Table 6 Comparison between performance of 3D reconstruction method used for volume estimation in the grading system (proposed method) and existing methods used for determination of fruit size

Method used for determination of fruit size	Fruits used in the experimentation	Dimension of technique	RMSE[a]	%RMSPE[b]
Optical ring sensor [28]	Kiwifruit	3D	1.8 mm	2.9
2D machine vision [7]	Pear	2D	4.1 ml	1.9
Stereo vision [21]	Apple	3D	6 ml	1.9
Orthographic silhouette based projection for volume [3]	Strawberry	3D	0.5-2 mm	2.5
Proposed volumetric 3D reconstruction method	Apple, mango, orange, pomegranate, strawberry	3D	$0.77 cm^3$	0.8

[a] RMSE: Value in mm in Root Mean Square. Error implies the error determined for equator of the fruit whereas value in ml and cm^3 implies the error measurement for volume of the fruit. [b] RMSPE: Root Mean Square Percentage Error

Table 7 Comparison between proposed grading system and existing systems on the basis of classification accuracy

Grading system	Fruits used in the experimentation	Color space	% accuracy in classification
Grading based on maturity [9]	Apple	RGB	95.83
Grading based on color [4]	Pomegranate	RGB	90.00
Grading based on ripeness [1]	Oil palm fruit	HSV	90.00
Grading based on color measurement [25]	Banana	HSV, CIE L*a*b*	97.00
Grading based on maturity [2]	Carambola	HSV	95.30
Proposed grading system based on volume and maturity	Apple, mango, orange, strawberry pomegranate	HSV	98.53

Table 8 Sensitivity analysis for volume parameter

Class	TP	FN	TN	FP	SE	SP
A	04	0	194	2	100.00	98.98
B	20	1	178	1	95.24	99.44
C	92	3	103	2	96.84	98.10
D	52	1	146	1	98.11	99.32
E	32	1	166	1	96.97	99.40

performance of the grading system. Table 6 compares performance of 3D reconstruction method used for volume estimation with some existing methods used for determination of the fruit size on the basis of evaluation parameters RMSE and RMSPE. The performance of the grading system is further compared with the performance of few existing grading systems in Table 7.

It can be clearly seen from Tables 6 and 7 that, the proposed volume and maturity based grading system outperforms the other methods. Most of the grading systems use a single view to extract color information of the fruit.

If self-occluding surface of the fruit has hue value deviated from the expected hue value, the grading system using a single image may not be able to detect it and grade the fruit incorrectly as matured fruit. On the other hand, the multiple-camera system acquires multiple images covering the entire surface of the fruit for determining the color and maturity of the fruit with greater accuracy. This improves the overall accuracy of the grading system.

The performance of the grading system is also analyzed for its computational complexity and sensitivity to the number of images. The computation time needed for the complete

Table 9 Sensitivity analysis of the grading system

Grades	TP	FN	TN	FP	SE	SP
G1	20	1	177	2	95.24	98.88
G2	36	1	162	1	97.30	99.39
G3	100	2	96	2	98.04	97.96
G4	24	0	175	1	100.00	99.43
G5	20	1	178	1	95.24	99.44

Table 10 Sensitivity analysis for maturity parameter

Maturity	TP	FN	TN	FP	SE	SP
Matured	184	2	12	2	98.92	85.71
Raw	16	1	182	1	94.12	99.45

TP True Positive, *FN* False Negative, *TN* True Negative, *FP* False positive, *SE* Sensitivity, *SP* Specificity

grading process includes the time needed for 3D reconstruction, the time needed for determination of maturity and the time needed for classification of the fruit. Since the cameras are calibrated after installation of the setup only once, the camera calibration process does not contribute to the time needed for grading the fruit. The average computation time for the grading process with six views is about 5.4 s. Tables 8, 9, and 10 provides parameter sensitivity analysis of the grading system. 'One at a time' (OAT) approach is used for performing the parameter sensitivity analysis. Thus, while performing the sensitivity analysis for volume, the maturity parameter is kept constant and vice versa. It is observed that the average sensitivity of the grading system is 97.16%. It is also observed that the computation time is sensitive to the number of images. The relation between computation time and number of images of a fruit sample is given in Fig. 13. Equation (7) is used for determining sensitivity and specificity of the fruit grading system. The accuracy of volume estimation depends upon the accuracy of camera calibration. The accuracy decreases with decrease in the number of views.

$$Sensitivity\ SE = \frac{TP}{TP + FN} \times 100 \qquad and \qquad Specificity\ SP = \frac{TN}{TN + FP} \times 100 \quad (7)$$

The grading system is also analyzed for its failure. The failure rate is about 1.45%. The failure in correct grading is observed for the boundary cases where the maturity value of the fruit is deviated by ±0.5% of the threshold. It is observed that the system may fail to determine the maturity if the illumination is not uniform. Moreover the system may fail to estimate the volume with reasonable accuracy if the number of views of the object is less than six and if the fruits have deep concavities.

The proposed volumetric 3D reconstruction method computes the volume of the fruit with high accuracy. Increase in number of views improves the accuracy of the grading system. However, this also increases the computation time. In future, the time required for the volume

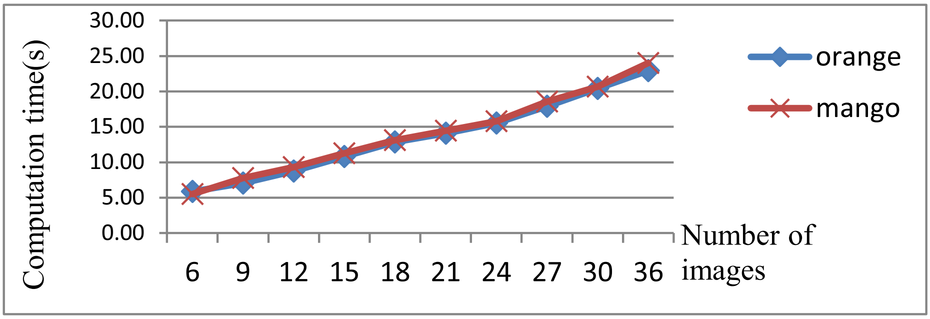

Fig. 13 Relation between computation time and number of images

estimation can be reduced to reduce the overall computation time. Hence in order to make the system realizable in real time, further improvement in the computation time is needed.

5 Conclusion

The paper presents a nondestructive and accurate fruit grading system using volume and color based maturity feature implemented using Fuzzy Rule Based Classification (FRBC) technique. Details of the 3D reconstruction pipeline and flow diagram for the grading system based on Fuzzy Inference System are described step by step with the results. The method estimates the volume of the fruit using volumetric 3D reconstruction method employing multiple cameras with high accuracy. The system computes the percentage of the matured region from the entire surface of the fruit using multiple images as against a single image used in the most of the 2D techniques. This overcomes the problem of determining the percentage of matured region of self occluding surface to improve the accuracy in maturity estimation. Stereo approaches available in the literature are computationally complex. They face challenges in reconstruction of the objects which have very few surface features such as fruits. On the other hand, the reconstruction method discussed in the paper reconstructs the fruits with arbitrary shapes in order to estimate their volume with high accuracy. This makes the grading system more robust and dynamic. The experimental results and comparison of the performance with the existing approaches show that the proposed method outperforms the other methods based on 2D techniques as well as 3D techniques. The proposed reconstruction method may face challenges if the object has deep concavities in the surface. However, this may not cause any limitation in the application of the fruit grading as most of the fruits in the nature do not have deep concavities in the surface. However, for realizing the system in real time, further improvement in the computation time is needed. In future, the time required for the estimation of the fruit volume using 3D reconstruction can be reduced to reduce the overall computation time.

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