Development of Machine Vision System for Size Classification of Potatoes (*Solanum tuberosum* L.)

Erwin P. Quilloy[1], Paolo Rommel P. Sanchez[1], Luther John R. Manuel[2] and Eunice M. Renovalles[3]

[1]Assistant Professor 1, Agricultural Machinery Division, Institute of Agricultural Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños, 4031 College, Laguna, Philippines (Author for correspondence email: epquilloy@up.edu.ph)

[2]University Researcher II, Agricultural and Bio-Process Division, Institute of Agricultural Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños, 4031 College, Laguna, Philippines

[3]Lecturer, Agricultural Machinery Division, Institute of Agricultural Engineering, College of Engineering and Agro-Industrial Technology, University of the Philippines Los Baños, 4031 College, Laguna, Philippines

ABSTRACT

Machine vision was explored in this study to characterize potatoes that are locally available in the Philippines based on the Philippine National Standards (PNS). A machine vision hardware was fabricated and its software was developed using LabVIEW for estimating the weight of potato and classifying them according to PNS. A weight estimation equation was determined by conducting polynomial regression analysis on the weight and projected area from 155 potato samples. Furthermore, test for measurement consistency was done to evaluate the capability of the developed MVS software to yield consistent readings on thirty sampling angles. Fifty potato samples were used on testing for sorting accuracy. Results of testing yielded a high R^2 value of 98.86% with p-value of 2.2 x 10^{-16}. Moreover, results revealed a low coefficient of variation of 0.33% and had no significant difference at α= 5%. Test for accuracy, on the other hand, exhibited a computed individual accuracy of 96.2% on the medium size, and 100% on the rest. Overall accuracy of the developed MVS software was computed at 98%, where the incorrect classification was noted to occur near the boundary of the sizes. The developed MVS projected capacity was computed at 7200 samples per hour, excluding time to load and unload potatoes.

Keywords — machine vision system, size classification, potato sizing, computer vision, LabView

INTRODUCTION

Potato (*Solanum tuberosum* L.) is one of the root crops popularly grown in 130 countries across the world. In the Philippines, it is considered as one of the high value crops. Generally, potatoes are cool-season crop grown in areas with high elevation ranging from 1000 to 8000 meters above sea level. (Gonzales *et al.*, 2016). The production of potatoes in the Philippines was around 110,752 MT in 2007. These were sourced from four main growing areas which include Cordillera Administrative Region (85%), Davao (8.3%), Northern Mindanao (5.7%) and SOCCSKSARGEN region (0.48%). Despite this volume of potatoes produced in 2007, the Philippines still imported around 46,887 MT of potatoes to meet the high demand both for consumer and industrial application for processing and service industries (Wustman *et al.*, 2010). From 2010 to 2014, the production trend of potatoes in the Philippines is about 120, 335.28 MT (Gonzales *et al.*, 2016).

The tubers of the potatoes, which are the consumed part of the crop, are graded according to size or weight. According to the Philippine National Standards (2007), the potatoes can be classified from very small or marble, to jumbo (Table 1).

Sizing of potatoes is usually done manually, either by visual inspection or by passing the harvested crop through sieves. When done by visual inspection, problems with inconsistencies arise due to varying human eye perceptions as well as fatigue. While mechanical grader offers higher efficiency in sorting, damages to the potatoes which resulted abrasion of surfaces to were noted to be higher, particularly in higher prime mover speeds (Valentin *et al.*, 2016). Use of machine vision addresses the visual inconsistencies as well as improve the efficiency of sorting by providing consistent judgement based on estimated parameters (Quilloy and Bato, 2015).

Machine vision has been used extensively in agricultural applications, mainly for quality inspection and grading of produce. Many researches explored the optimum threshold value for processing the images obtained. In 2008, Rios-Cabrera *et al.* conducted a study which made use of machine vision to extract some properties of potatoes. Their study explored artificial neural networks (ANN's) for detecting misshapen potatoes. Overall classification accuracy of their developed software was observed to be 93.8%.

Furthermore, a study done by Wang *et al.* (2011) made use of machine vision system to detect the size of potato based on centroidal principal axis. The algorithm to determine the major axis and minor axis lengths was developed using MATLAB. Results of their study yielded relative error of 6.08% and 7.42% for the major and minor axes, respectively.

Moallem *et al.* (2013) conducted a study for detecting potato defect using neural networks and support vector machine algorithms to develop a machine vision software. Evaluation of their developed software revealed a detection rate of 96.7%. In 2014, another study developed by Moallem *et al.* integrated image processing with fuzzy inference system for segmenting images of potatoes. Their system yielded 98% accuracy in producing segmented images. Such images are to be used in further processing in a machine vision system.

Another study conducted by Caprara and Martelli (2015) employed machine vision in the evaluation of external damage of potatoes. Monochromatic images of potatoes were obtained and processed. The developed system yielded 100% accuracy in recognizing external defects. In the same year, Liao *et al.* (2015) developed a machine vision software for detecting potato shapes and evaluating size of potatoes using ellipse axis method with accuracies of 98.8% and 93%, respectively. In a similar study done by Brar and Singh (2016), a software yielding 90% accuracy in detecting defects like cracks and rots.

Grading of potatoes based on size depends on the local standards for classifying the tubers. In the Philippines, machine vision system for sorting potatoes is not yet widely explored. The study aimed to develop a machine vision system for size classification of local potatoes.

Table 1. Size classification of potatoes based on weight (Source: PNS, 2007)

SIZE	WEIGHT (g)
Very small or marble	< 50
Small	50 – 100
Medium	101 - 150
Big	151 – 200
Large	201 – 250
Extra large	251 – 300
Super	301 – 350
Jumbo	> 350

METHODOLOGY

Machine Vision System (MVS) Set-up

The MVS was composed of a light chamber, web camera, laptop computer and software. The platform of the light chamber at which the potatoes were placed was covered with a white board to provide optimum contrast between the background and sample. Similarly, the top and side panels of the light chamber were also covered with a white board to prevent ambient lighting illumination. The sample was illuminated using a 22-watt fluorescent ring light which provided a color temperature of 5400K. The light source was mounted on the top side of the light chamber and delivered 800 lux at 45 cm distance from the platform. 30-frames per second videos were captured using a 16-megapixel web camera which communicated with the computer via USB port and was mounted 41.5 cm from light chamber platform. On the other hand, the laptop computer was equipped with Intel Core i5-2435M at 2.5 GHz CPU and 4GB DDR3-1333 RAM. The operating system of the computer was a Microsoft® Windows® 7. Figure 1 summarizes the hardware and software components of the MVS as well as the positions of the potato during video capture.

Machine Vision System (MVS) Software Development

The software was developed using National Instruments LabVIEW 2010 with Vision Development Module (VDM). The VDM provided built-in real-time vision processing functions which were used by the software to communicate with the camera, extract color-channels and perform image segmentation, binary image processing, and feature extraction.

To obtain the grade size and actual weight of a single potato, the software captured real-time video feed from the camera using the image acquisition function. The blue-color channel of the video was then extracted using the blue plane extraction function to generate an 8-bit video of the sample. Using inter-class variance method and specifying dark object detection, the software automatically determined the threshold value and segmented the object from the background. The resulting binary image was then morphologically transformed using the closing algorithm to smoothen the counters and fuse the narrow breaks (Razmjooy *et al.,* 2012). The fill holes algorithm was used to cover the gaps within the image, after which area determination, in pixels, of the object was determined using particle analysis, a built-in function of VDM which yields pixel count, area, perimeter, center of mass, and other geometric parameters. The resulting pixel count was then used by the mathematical model to give the estimated weight of the potato. Finally, the estimated weight was then compared to the standard classification scheme as stated in PNS/BAFPS 53:2007 to determine the grade size. Figure 2 summarizes the grading workflow that was used by the software.

Modeling of Weight Estimation Equation

A total of 155 samples composed of potato sizes including marble, small, medium, big, large, extra

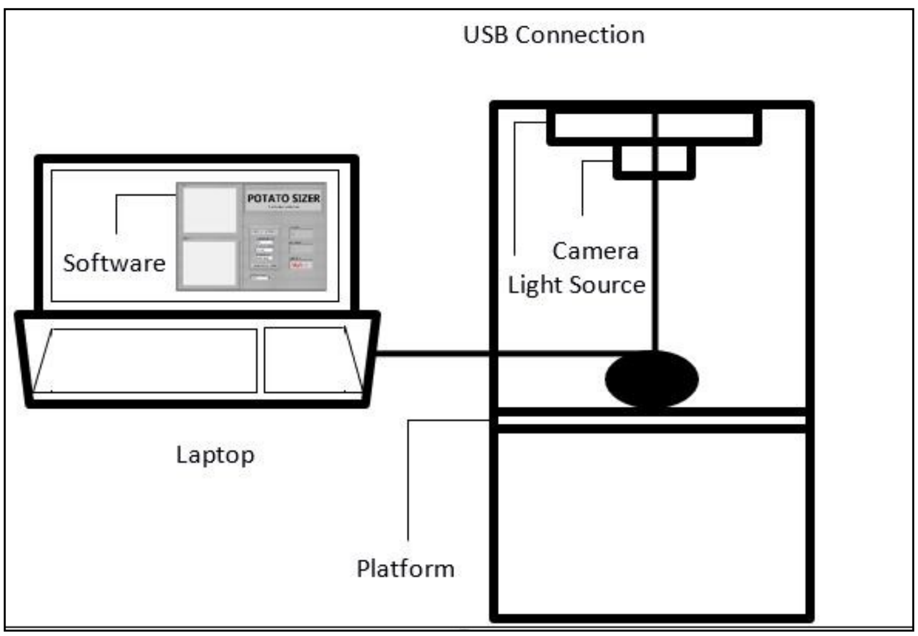

Figure 1. MVS components and the relative position of the potato sample to the camera.

large, super and jumbo were weighed using an OHAUS GT4100D top loading balance. The same samples were then placed inside the light chamber of the MVS to measure their projected area in pixels. A second-degree polynomial regression model relating the top area projection of potato (A), in pixels, and weight (W), in grams, was obtained expressed using the equation:

$$W = C_1A^2 + C_2A + C_3 \qquad \text{Equation 1}$$

where C_1, C_2, and C_3 are coefficients of each term in the equation.

Testing of Developed Machine Vision System Software

Two test methods were performed to determine the overall reliability of the system: (a) test for measurement consistency and (b) MVS weight and size classification performance. Test for measurement consistency determined if there were differences in the MVS weight measurements at different angular orientations of the sample. On the other hand, evaluation of size classification performance was conducted to determine the actual performance of the system in weight measurement and size classification of random samples of potato.

Test for Measurement Consistency

A randomly selected potato was placed inside the light chamber for processing by the software. The estimated weight of the potato was obtained at each sampling point starting at zero (0) degree position. The potato was then rotated at 12-degree interval, at which estimated weight was obtained for each position until it reached the last sampling point which is 348-degree. A total of thirty sampling angles were selected from which the weights were obtained. The process was conducted for three trials, after which, the mean, SD, and CV were then computed. The results were subjected to ANOVA at 5% level of significance to determine the effect of angular orientation to the projected weight of the potato.

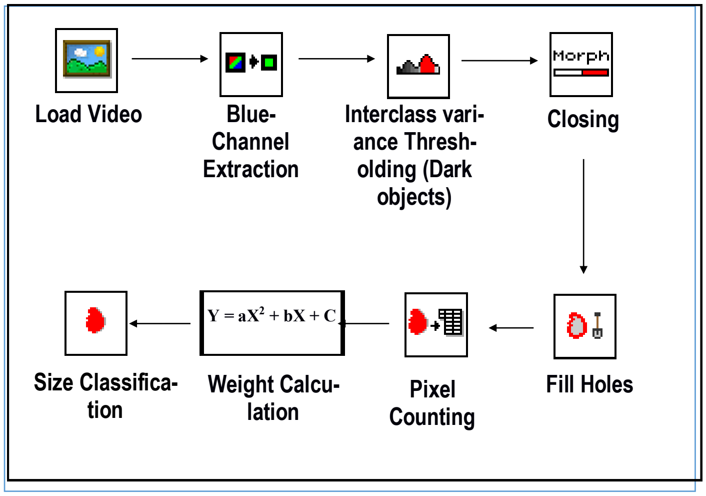

Figure 2. Sizing workflow and vision functions that were used by the machine vision software.

Figure 3. MVS setup

Weight and Size Classification Performance

The weight and size classification of 50 randomly selected samples were obtained using the developed MVS software. After which, the samples were then weighed using the top load balance and classified according to the PNS/ BAFPS 53:2007. The results were tabulated in the sorting performance matrix and then the individual accuracy or the accuracy for each size classification was computed. Overall accuracy was then calculated. The general formula for accuracy is:

$$\% acc = \frac{correct}{N} \times 100 \qquad \text{Equation 2}$$

where *% acc* is the accuracy in percent, *correct* is the number of correctly classified samples, and *N* is the total number of samples.

RESULTS AND DISCUSSION

Development of the Machine Vision System Software

The developed software was designed to keep the interface simple (Figure 3 and 4). Picture boxes for the raw image and processed image were provided. Drop down menu controls were also featured to easily manipulate the image segmentation process as well as for selecting the camera connected to the system. Text boxes for the obtained data which include projected area, estimated weight and size classification served as containers for the data.

As shown in Figure 5, the blue channel exhibited the widest difference between the object and background pixels; thus, being selected as the

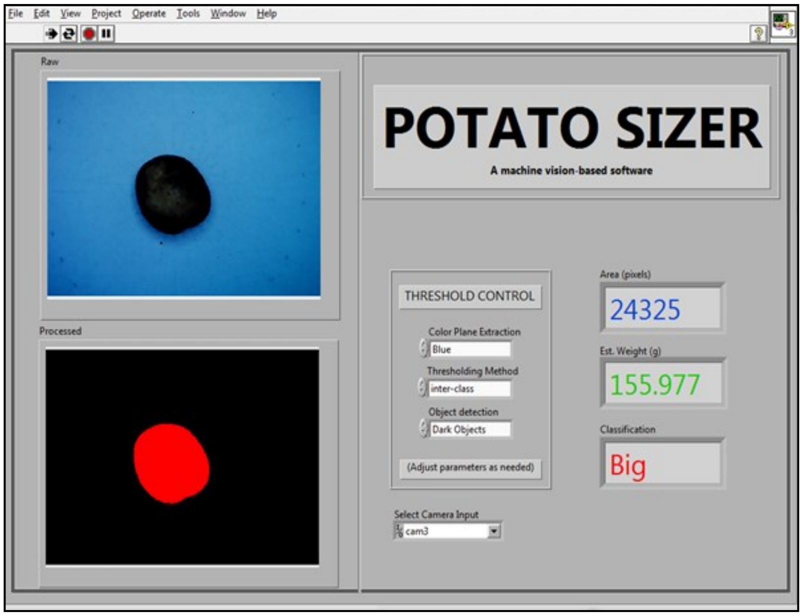

Figure 4. Front panel of the developed machine vision system software.

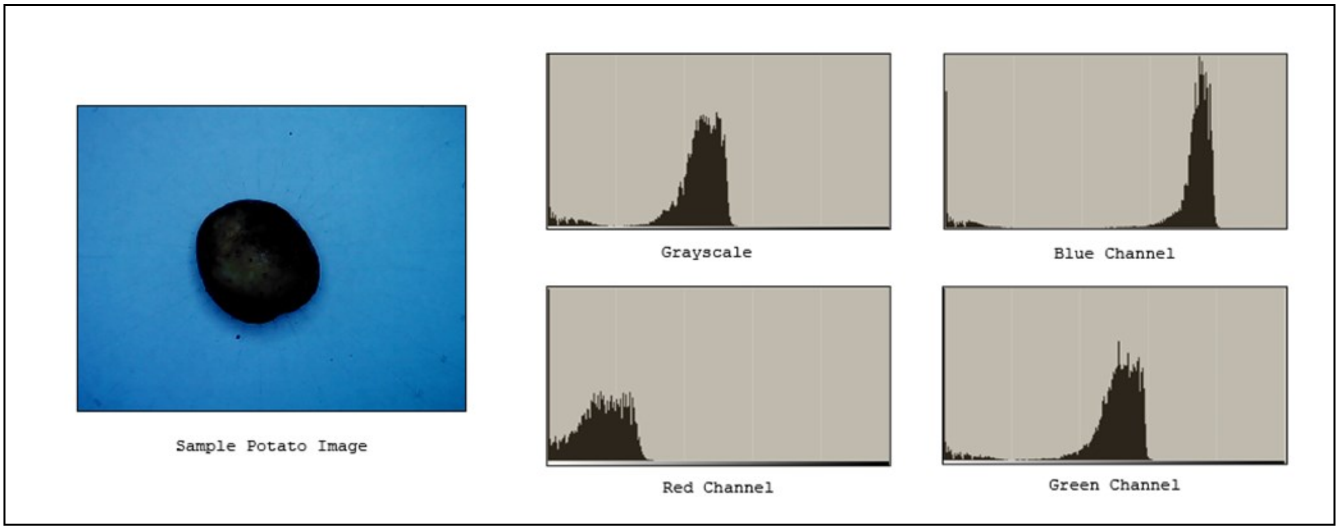

Figure 5. Sample potato image with its respective histogram at grayscale, red channel, green channel and blue channel.

channel for binarization. This large difference was a result of low color temperature setting of the webcam as seen in the white background appearing with a shade of blue in the sample image. However, to facilitate other cases, a dropdown control was included in the software interface which will allow selection among gray-scale, red channel, green channel or blue channel as reference for binarization.

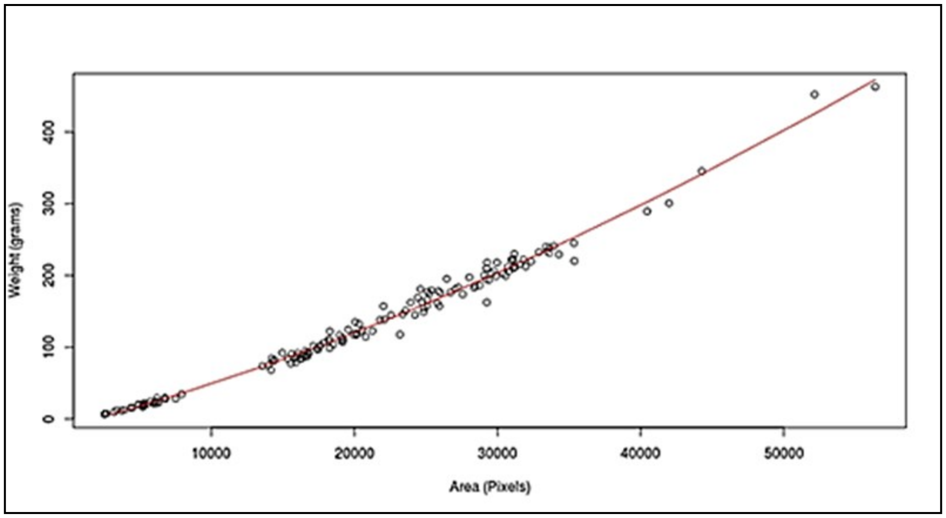

Figure 6. Line fit plot for the polynomial regression analysis second order).

Weight estimation model

Weights and projected areas obtained from the 155 samples were used as parameters for the calibration process to formulate the weight estimation equation. Results of the regression analysis showed a coefficient of determination (R^2) value of 0.9886, indicating that 98.86% of the variation in the weight can be explained by the variation in projected area with p-value (2.2×10^{-16}). Based on the line fit plot (Figure 6), it was observed that the weight had a positive relationship with the projected area. It is because that heavier potatoes tend to be bigger in size thus larger projected area. Regression analysis yielded the second order polynomial equation as shown in Equation 3:

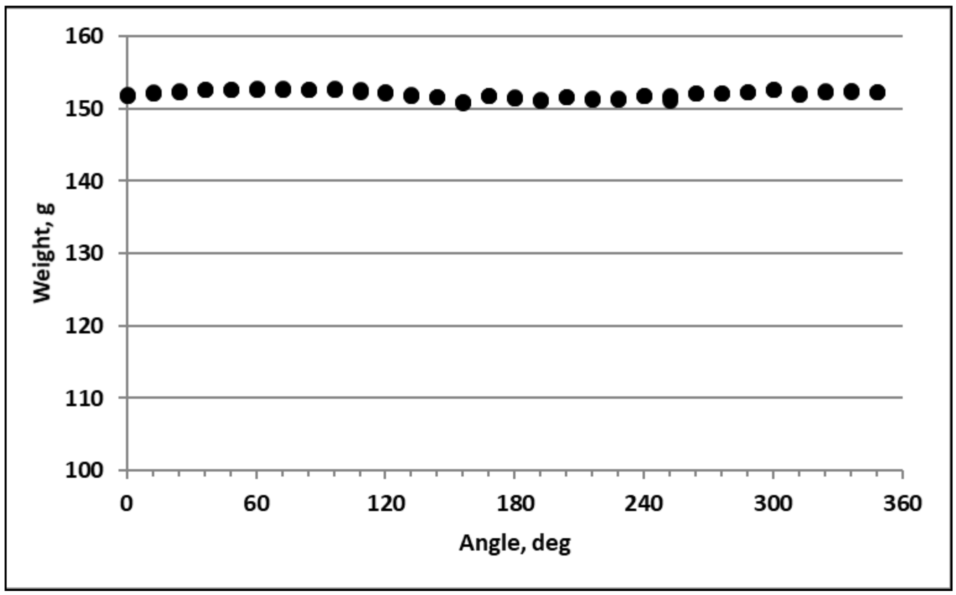

Figure 7. Weight measurements of the sampled potato at each sampling angle of 12-degree interval.

Table 2. Test for measurement consistency summary.

	TRIAL 1	TRIAL 2	TRIAL 3	AVER-AGE
Mean (g)	151.11	151.11	151.13	152.11
SD (g)	0.53	0.50	0.51	0.51
CV (%)	0.33	0.33	0.33	0.33

Table 3. Sorting performance of the developed software.

ACTU-AL	CLASSIFICATION								No. of Sam-ples	% Accu-racy
	Marble	Small	Medium	Big	Large	Extra large	Super	Jumbo		
Marble	8	0	0	0	0	0	0	0	8	100
Small	0	4	0	0	0	0	0	0	4	100
Medium	0	1	25	0	0	0	0	0	26	96.2
Big	0	0	0	4	0	0	0	0	4	100
Large	0	0	0	0	0	0	0	0	0	---
Extra large	0	0	0	0	0	4	0	0	4	100
Super	0	0	0	0	0	0	3	0	3	100
Jumbo	0	0	0	0	0	0	0	1	1	100

$$W = 6 \times 10^{-8} A^2 + 0.045\,A - 10.88 \qquad \text{Equation 3}$$

where W is the estimated weight in grams and A is the projected area of the potato in pixels. This equation was integrated into the developed software.

Test for Measurement Consistency

Data obtained from 30 different angles Table 2 revealed that the average mean for the three trials was 152.11 g with corresponding standard deviation of 0.51 g. The obtained coefficient of variation (CV) for the three trials was 0.33 % as observed from the obtained weight measurements at different sampling angles (Figure 7). Subjecting the weight measurement results to ANOVA showed that there was no significant difference among different readings at different angular orientation and among the trials at 5% level of significance.

Size Classification Performance

The developed MVS software classified the potatoes according to the PNS/BAFPS 53:2007. Based on the output of sorting 50 potatoes, it was noted that the software misclassified the medium sized potato as small. This error was observed to occur near the boundary. However, the individual accuracy of the software in classifying was observed to be high on all sizes as shown in Table 3, with 96.2% for the medium size classification being the lowest and 100% for other size classifications. Overall accuracy of the software was computed to be 98%.

Furthermore, it was noted that the time consumed to classify a potato sample was 0.5 second. This excluded the time spent to load a sample into the vision chamber and unload the sample from it. Thus, the projected capacity of the developed software to classify potatoes according to size from loading to processing of image was computed to be 7200 potatoes per hour.

CONCLUSION

A machine vision system was developed in this study to characterize the size potatoes according to the Philippine National Standards. LabVIEW software was used to develop a MVS software for estimating the weight of potato as well as classifying them according to the local standards. Test for measurement consistency was done to evaluate the capability of the developed MVS software to yield consistent readings. ANOVA results revealed that there was no significant differences among the readings obtained from 30 different orientations at the computed coefficient of variation of 0.33% and 5% level of significance. Computed individual accuracy was noted to be 96.2% on the medium size, and 100% on the rest. Overall accuracy of the developed MVS software was computed to 98%, where the incorrect classification was noted to occur near the boundary of the sizes. The developed MVS projected capacity was computed to be 7200 samples per hour.

RECOMMENDATIONS

It is recommended to integrate the MVS in a conveyor type assembly such that the actual capacity of the system can be evaluated in dynamic setup. Furthermore, the use of faster image acquisition devices in dynamic set-ups will allow the MVS to operate at higher conveyance speeds as it can capture sharper images without noise or errors in image processing.

LITERATURE CITED

BRAR, E.S. and K. SINGH. (2016). Optimum threshold value to segment potato image in hand-held potato grading machine. IOSR Journal of Computer Engineering (IOSR-JCE). e-ISSN: 2278-0661, p-ISSN: 2278-8727. Special Issue - AETM'16. pp 94-99.

CAPRARA, C. and R. MARTELLI. (2015). Image analysis implementation for evaluation of external potato damage. Applied Mathematical Sciences. 9(81): 4029-4041

GONZALES, I.C., C.G. KISWA and A.B. BAUTISTA. (2016). Sustainable potato production in the Philippine Cordillera Region. International Journal of Engineering and Applied Sciences (IJEAS) ISSN: 2394-3661. 3(6): 29-37.

LIAO, G., X. WANG, J. JIN and J. LI. (2015). Potato size and shape detection using machine vision. MATEC Web of Conferences. 31. 15003. 5p.

MOALLEM, P., N. RAZMJOOY and M. ASHOURIAN. (2013). Computer vision-based potato defect detection using neural networks and support vector machine. International Journal of Robotics and Automation. 28(2): 137-145.

MOALLEM, P., N. RAZMJOOY and B.S. MOUSAVI. (2014). Robust potato color image segmentation using adaptive fuzzy inference system. Iranian Journal of Fuzzy Systems. 11(6): 47-65.

PHILIPPINE NATIONAL STANDARDS. 2007. Fresh vegetables – Potatoes – Grading and classification. PNS/BAFPS 53:2007. 7p.

QUILLOY, E.P. and P.M. BATO. (2015). Machine vision-based software for automating the grading process of Philippine table eggs. Philippine Agricultural Scientist. ISSN: 0031-7454. 98(2): 148-156.

RAZMJOOY, N., B. SOMAYEH MOUSAVI and F.SOLEYMANI. (2012). A real-time mathematical computer method for potato inspection using machine vision. Computers & Mathematics with Applications. 63(1): 268-279.

RIOS-CABRERA, R., I. LOPEZ-JUAREZ and H. SHENG-JEN. (2008). ANN analysis in a vision approach for potato inspection. Journal of Applied Research and Technology. 6(2): 106-119.

VALENTIN, M.T., E.M. VILLOTA, V.U. MALAMUG and I.C. AGULTO. (2016). Evaluation of a helix type potato grader. CLSU International Journal of Science and Technology. 1. 10.22137/ijst.2016.v1n1.05.

WANG, C., X. LI, W. WANG, J. LIU, H. TAO and D. WEN. (2011). Detection of potato's size based on centroidal principal axis. African Journal of Agricultural Research Vol. 6(17): 4140-4148.

WUSTMAN, R., L. FRANKE, A. HAVERKORT and F.P. KOESVELD. (2010). Final report Philippine Potato Project 2009-2010: Compilation of visit reports. Wageningen, DLO Foundation. 57 p. ■