Seed sizing from images of non-singulated grain samples

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Shahin, M.A. and Symons, S.J. 2005. **Seed sizing from images of non-singulated grain samples.** Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **47**: 3.49 - 3.55. Image analysis is a strong candidate for developing automated measurement systems for seed sizing. A unique image analysis (IA) based approach to measuring seed size from non-singulated samples is presented in this paper. The IA method was tested on four types of grains differing in seed size, shape, and colour. IA determined seed sizes closely matched those determined by manual sieving both in average seed size and the size distribution for seeds of spherical as well as non-spherical shape. The IA method was found to be highly repeatable and much faster than the sieving method. Between and within operators' differences were statistically insignificant ($p > 0.05$) for both the methods. The IA method took less than 30 seconds to measure one sample as opposed to over 10 minutes for manual sieving. **Keywords**: seed sizing, image analysis, sieving.

L'analyse d'images est un outil prometteur pour le développement de systèmes automatisés pour le tri de semences. Une approche novatrice basée sur l'analyse d'image (AI) pour mesurer la taille des semences provenant d'un échantillon non singulier est présentée dans cette publication. La méthode AI a été testée sur quatre types de graines différentes en termes de taille, forme et couleur. La taille des semences déterminée par AI correspondait étroitement à celle obtenue par tamisage manuel tant au niveau de la taille moyenne des semences que de la distribution de taille pour les semences de formes sphérique et non-sphérique. La méthode AI s'est avérée être reproductible et beaucoup plus rapide que le tamisage. Les différences entre opérateurs et pour un même opérateur étaient statistiquement non significative ($p > 0.05$) pour chacune des méthodes. La méthode AI nécessitait moins de 30 secondes pour l'évaluation d'un échantillon comparativement à plus de 10 minutes pour le tamisage manuel. **Mots clés**: tri de semences, imagerie, tamisage

INTRODUCTION

A number of pulse crops are grown in Canada including peas, lentils, beans, and chickpeas, which are valued and marketed based on appearance. While seed colour is an important grading factor, seed size is only specified for chickpeas (Grain Grading Guide, www.grainscanada.gc.ca), yet size profile or size distribution is significant for the seed companies and processing industry affecting product value. Export markets require uniform seed size. Variations in seed size affect the accuracy of planting (Anonymous 1998), de-hulling efficiency, and the quality of foods prepared from pulses (Personal communications: N. Wang, Research Scientist, Canadian Grain Commission, Winnipeg, MB). Uniformity of seed size influences optimal water absorption and the quality of the final product in food grade soybeans (Poysa et al. 2002) and other pulse grains. Screen sieving is widely used as a standard method of determining seed size distribution in grains. In a typical sieving practice, a set of screens with different hole sizes are used to separate seeds into various size categories. Round-hole screens are used for circular or approximately circular seeds (peas or soybeans) whereas slotted-hole screens are used for noncircular seeds (kidney or cranberry beans). Sieving, manual or mechanical, is known to be inconsistent, laborious, and time consuming. It may potentially cause involuntary damage to the seed coat, which can adversely affect the visual appearance, storability, and processing quality of the grains. A quick, efficient, and non-destructive method for determining seed size profiles would greatly benefit the grain industries. Machine vision or image analysis can be a faster, non-destructive alternative to the traditional sizing equipment currently used in the grain industry.

Several machine vision systems have been developed for characterization and classification of wheat varieties in the USA, UK, Canada, and Australia that were critically reviewed by Sapirstein (1995). Many researchers have used digital imaging to measure morphological features of various grains including wheat (Sapirstein et al. 1987; Symons and Fulcher 1988a, 1988b; Zayas et al. 1989; Keefe and Draper 1986; Myers and Edsall 1989; Shouche et al. 2001), oats (Pietrzak and Fulcher 1995; Westerlind 1988), rice (Sakai et al. 1996) and linseed (Keefe 1999). Steenhoek and Precetti (2000) used machine vision to classify seed corn into various size categories. Churchill et al. (1992) reported machine vision to be more accurate and efficient in measuring dimensions of seeds than trained inspectors working with microscopes.

In general, machine vision systems for grain characterization have been used under controlled laboratory conditions where well-separated seeds were manually placed on a plate or a tray for image-capture. Manual seed placement is tedious and time consuming especially when a large number of seeds in a representative sample of grains are to be analyzed. Automatic seed positioning systems for placing individual grain kernels under a camera for image acquisition have been developed (Casady and Paulsen 1989; Jayas et al. 1999). However, combining such a seed presentation device with the machine vision system would make the overall system more expensive and less portable.

Seed size determination based upon images of non-singulated samples is highly desirable; however, measuring size of each kernel in an image with touching and overlapping kernels is a challenge. Connected multiple kernels can lead to overestimation of the size measurements while failure to recognize occluded kernels can lead to underestimation of the size measurements. The problem at hand has two issues to deal with: (a) separating the touching objects; and (b) identifying and dealing with partially occluded objects. While working with the images of rock fragments, Maerz et al. (1996) used edge detection followed by a number of reconstruction techniques to form an 'edge net' to delineate object boundaries. Size measurements, however, were either underestimated due to partially overlapping fragments or overestimated due to 'missing or hidden fines' (Maerz and Zhou 1998). Similar image processing approaches are commonly used for measuring particle size distribution in material testing applications (Smolej 2001; www.archive4images.com/english/infomaterial/downloads; www.eaglabs.com/appnotes/AN345.pdf).

Shatadal et al. (1995) used mathematical morphology to separate touching grain kernels in an image. Shashidhar et al. (1997) used boundary sampling and ellipse fitting to identify and measure dimensions of touching kernels. In both these studies, separated and touching kernels with different orientation were manually placed for imaging. Performance of these algorithms was not tested for bulk grain samples. Shahin and Symons (2001) developed an imaging system for measuring seed size distribution from images of bulk lentils. Their approach was simple: morphological operations were used to separate seed boundaries; partially occluded seeds were 'washed out' by successive erosion followed by successive dilation to restore seed size. The outcome of their method closely matched the results from sieving and calliper measurements. Shahin and Symons (2003) used the same sizing algorithm to segregate different lentil varieties based on seed size and colour measured from bulk lentil images. As an extension to this work, the focus of this research was to develop a similar system capable of sizing grains of different shapes, size, and colour. While seed size is frequently used in commercial trade of pulse grains, it is not part of the Canadian Grain Commission (CGC) standards as there are issues with sieving techniques, screen manufacturing, and differences between imperial and metric measurements (Personal communications: Norm Woodbeck, Manager Quality Assurance Standards, CGC, Winnipeg, MB). The purpose of this work was to create and define standards, as there is no standard method for sieving. Specific objectives were:

1. To develop an IA system for measuring seed size (profile) from images of non-singulated samples of spherical and non-spherical seeds, and
2. To evaluate the performance of the IA system with respect to the current industry standard of sieving method in terms of accuracy, repeatability, and robustness.

MATERIALS and METHODS

Grain samples

Four types of grains differing in seed shape and colour were used as test objects - green and yellow peas (spherical), soybeans, and Kabuli chickpeas (non-spherical). Three samples for each of the four commodities provided by the Industry Services of the CGC from the crop year 2000 were analyzed. Following the industrial standard sampling protocol, soybean samples were 500 g each while samples of green peas, yellow peas, and chickpeas were 250 g each. In each case, selected samples represented different grades.

Seed size analysis

Each of the samples was analyzed for seed size using two methods of measurement (manual sieving and image analysis) for comparison. Three people (operators) used both methods for each sample. This provided data to investigate operator-to-operator variability. Sizing of each sample was repeated four times (except for chickpeas where only three replicates were possible due to the busy schedule of the operators) to study within operator variability. For both the methods, the average seed size, standard deviation, and size distribution were determined for each sample for comparison. The analysis of variance test was performed with PROC GLM (SAS release 8.02) to investigate method-to-method differences, operator-to-operator differences, and within operator differences for each commodity separately.

Sieve method

Each sample was manually sieved using a series of round-hole sieves differing in hole-size. Selecting an appropriate series of sieves for each sample and starting from the largest-holed sieve in the series, percentage of the seed remaining above a particular size of sieve was recorded to determine the size distribution. Following current Canadian industry practices, metric or SI sieves were used for chickpeas whereas imperial sieves were used for peas and soybeans. For chickpeas, a set of four metric sieves ranging in hole-diameter from 7 to 10 mm with an increment of 1 mm was used to create five size bins. For soybeans and peas, a stack of six imperial sieves with hole-diameter ranging from 14/64 inch (5.56 mm) to 19/64 inch (7.54 mm) with an increment of 1/64 inch (0.3968 mm) was used to generate seven size bins. Average seed size and standard deviation for each sample were derived from the respective size distribution histograms by using standard statistical formulae (Snedecor and Cochran 1989). Data from imperial sieves were converted to equivalent SI units for comparison.

Image analysis (IA) method

Each sample was imaged using a flatbed scanner (ScanMaker 4, Microtek, Denver, CO) for subsequent analyses. Initially, the same sample presentation and image processing procedures were used as for lentils (Shahin and Symons 2001). That is, a bulk sample dumped in a clear plastic tray was imaged and successive erosion dilation operations were used to separate seed boundaries for size measurements. Preliminary analysis revealed that the method developed for lentils worked well for the spherical yellow and green peas, however, it gave erroneous results for the elliptical soybean and convoluted chickpea seeds. Both sample presentation and the seed boundary separation algorithm needed modifications for soybeans and chickpeas to correct for variations in seed orientation among re-pours of the same sample and information loss due to changes in shape resulting from image processing to separate seed boundaries. The issue of seed orientation was more profound in soybeans where a bulk poured sample did not facilitate the ellipsoid beans falling with their longest axis in the plane of the image. Re-pours of the same sample differed by up to 15% in the predominant size range (Fig. 1a). To allow the soybean seeds to orientate on the scanner, a loosely packed single layer was used which, in conjunction with the modifications to the seed boundary detection algorithm discussed later in the paper, lowered the between scans variations to within 6.4% (Fig. 1b).

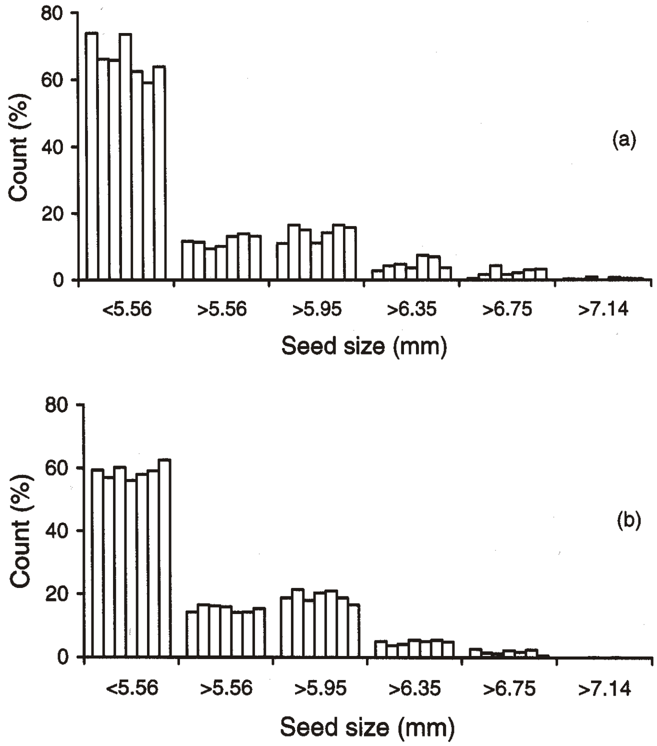

Fig. 1. Size measurements from repeated scans of a soybean sample for different methods of seed presentation: (a) bulk pour, (b) single layer.

In the case of chickpeas, complex shape and surface characteristics posed difficulties in seed boundary separation. Boundary separation is key to accurate measurements of seed size from images of bulk samples or touching kernels. Kabuli chickpeas, ranging from near spherical to quite irregular in shape, have a slight projection where the seed is attached to the mother plant (Fig. 2). This tiny projection has to be included in the measurement, as it is known to significantly affect mechanical sieving. Also, the colour variation within a chickpea seed (or any seed in general with surface discoloration due to weather damage) made the boundary separation challenging - a simple sequence of erosion dilation over-eroded the blobs with 'holes' representing seeds with dark brown spots. As a result, the imaging approach to detect seed boundaries accurately was modified significantly as described later, and it was more complex than used for lentils by Shahin and Symons (2001). The modified algorithm separated boundaries while preserving the shape of the seeds.

For imaging, thoroughly mixed bulk samples were poured into a clear-plastic tray (200 x 200 x 25 mm) as a single layer such that the seeds lay on the tray in a natural orientation with minimal overlap. The sample filled tray was placed on the scanner bed and an 800 by 800 pixel window centred at the field of view was captured. In the case of peas and chickpeas, standard samples of 250 g each covered the sample tray as a single layer. For soybeans, approximately 200 g filled the tray as a single layer requiring a representative sub-sample to be imaged in this case. All the images were captured at a resolution setting of 100 dots per inch resulting in a spatial resolution of 0.254 mm per pixel. The scanner was geometrically calibrated using a grid of known dimensions. An image analysis library package (KS400, Carl Zeiss, Oberkochen, Germany) was used for processing these images and measuring image features of interest. Seed separation was accomplished through iterative application of erosion-dilation operations. The following steps were undertaken to measure seed size from non-singulated samples:

1. Background shadows were removed using a histogram-based threshold and a binary image was created using adaptive grey-value segmentation. This localized segmentation separated boundaries of most seeds that were slightly touching in the original image. These singulated seeds were separated from the processed image based on a predefined shape factor in terms of circularity and copied to a 'mask' image in order to avoid unnecessary processing of blobs that were already separated. The KS function FCIRCLE, as defined in Eq. 1, was used as a measure of circularity.

$$FCIRCLE = 4\pi \frac{Area}{Perimeter^2} \tag{1}$$

The value of FCIRCLE approaches 1 for a circular region. The size of these singulated seeds was measured as a preliminary size estimate to set size limits for separating remaining difficult-to-separate touching seeds and to eliminate unwanted smaller or larger than usual blobs representing partially occluded seeds, over-eroded blobs due to surface discolouration of seeds, or still remaining multiple seeds.

2. Selecting an appropriate structuring element based on the preliminary size estimate, successive application of an erosion-scrap-dilation sequence of operations was performed to separate remaining touching seeds. Scrap, an area based threshold operation, eliminated unwanted smaller objects representing occluded seeds. Dilation reinstated the original size of the image blobs representing seeds. At the end of each erosion-scrap-dilation cycle, blobs in the image were

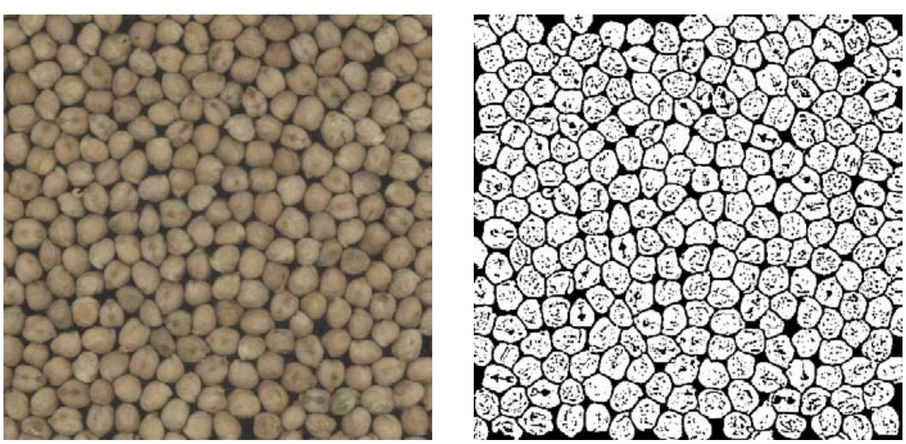

Fig. 2. Seed boundary separation for size measurement from bulk samples.

Table 1. Mean seed size and standard deviation from three operators with four replicates (three replicates for chickpeas).

Samples	IA Mean (mm)	IA SD (mm)	Sieve Mean (mm)	Sieve SD (mm)	Error* (%)
Green pea 1	6.49	0.031	6.51	0.043	-0.31
Green pea 2	6.33	0.031	6.24	0.023	1.44
Green pea 3	6.29	0.058	6.17	0.026	1.94
Yellow pea 1	6.65	0.039	6.62	0.011	0.45
Yellow pea 2	6.75	0.039	6.70	0.039	0.75
Yellow pea 3	6.83	0.042	6.81	0.027	0.29
Soybean 1	6.33	0.024	6.33	0.020	0.00
Soybean 2	5.97	0.032	6.08	0.017	-1.81
Soy bean 3	6.40	0.036	6.31	0.087	1.43
Chickpea 1	8.70	0.052	8.76	0.061	-0.68
Chickpea 2	8.49	0.037	8.66	0.033	-1.97
Chickpea 3	8.89	0.025	8.64	0.030	2.89

* Difference between the mean size values obtained form IA and sieving methods as percent of the sieving value.

evaluated for single seed criteria based on shape factor and seed size limits set by preliminary size estimates. Separated seeds were copied to the mask image and remaining touching seeds were processed further. This process continued until all the seeds were separated and copied to the mask image for size measurements (Fig. 2b). Prior to size measurements, each blob in the mask image was checked again for single seed criteria to make sure that only the objects representing single seeds were measured.

3. Appropriate size parameters of the objects in the mask image were measured. For spherical objects such as peas, effective diameter (DCIRCLE in KS) was measured as the seed size. DCIRCLE is defined as the diameter of a circle with the area equivalent to that of a region. For non-spherical objects such as soybeans and chickpeas, minimum dimension of the regions representing seeds (FERETMIN in KS) was measured as the seed size. Minimum dimension was selected as this typically reflects the limiting size of non-spherical seeds to passing through a mechanical sieve. This can be further compounded by shape. From these measurements, average seed size, standard deviation and size histograms were determined for data analysis and comparison with the results from sieving method.

RESULTS and DISCUSSION

The proposed IA method effectively separated seed boundaries making seed measurements from the bulk sample possible. Figure 2 shows an image of chickpea seeds before and after image processing. Seed boundaries were separated and unwanted blobs representing partially occluded seeds were removed. Seed shape was preserved. Similar outcomes were observed and validated for the images of the other commodities by overlaying the original and mask images. The average seed size measured with IA closely matched the sieving method for all the samples tested (Table 1). A maximal discrepancy of 0.25 mm was observed for chickpea sample 3 where the IA method measured one pixel bigger than the sieve method. Overall, the error/difference in mean values with respect to sieving results was within 3% (1.2% on average) and standard deviations in both the methods were comparable. These errors are much smaller than reported earlier by Maerz et al. (1996) of up to 10% for medium graded crushed limestone aggregates and overestimation by 20% for pea gravel without calibration (within 4% of sieving values after calibration).

Analysis of variance test showed that the two approaches to seed sizing overall were statistically no different for all the four commodities tested ($p > 0.29$ for the model, Table 2). The two methods of measurement (IA or sieving) were statistically the same for the non-spherical soybean and chickpea seeds ($p > 0.8492$) but diverged slightly for spherical seeds in green and yellow peas ($p \sim 0.05$). Between operators and within

Table 2. ANOVA results.

Commodity	Source	DF	Sum of squares	Mean square	F Value	Pr > F
Green pea	Model	6	0.10402087	0.01733681	1.04	0.4098
	Method	1	0.07269244	0.07269244	4.35	0.0410
	Operator	2	0.02474614	0.01237307	0.74	0.4811
	Replicate	3	0.00658229	0.00219410	0.13	0.9412
	Error	65	1.08679134	0.01671987		
	Total	71	1.19081222			
Yellow pea	Model	6	0.05333333	0.00888889	1.25	0.2945
	Method	1	0.02568889	0.02568889	3.60	0.0621
	Operaror	2	0.02730000	0.01365000	1.91	0.1557
	Replicate	3	0.00034444	0.00011481	0.02	0.9972
	Error	65	0.46346667	0.00713026		
	Total	71	0.51680000			
Soybean	Model	6	0.03204722	0.00534120	0.19	0.9783
	Method	1	0.00050139	0.00050139	0.02	0.8939
	Operator	2	0.02840833	0.01420417	0.51	0.6042
	Replicate	3	0.00313750	0.00104583	0.04	0.9902
	Error	65	1.81834028	0.02797447		
	Total	71	1.85038750			
Chickpea	Model	5	0.00896481	0.00179296	0.10	0.9920
	Method	1	0.00066852	0.00066852	0.04	0.8492
	Operator	2	0.00427037	0.00213519	0.12	0.8901
	Replicate	2	0.00402593	0.00201296	0.11	0.8961
	Error	48	0.87833333	0.01829861		
	Total	53	0.88729815			

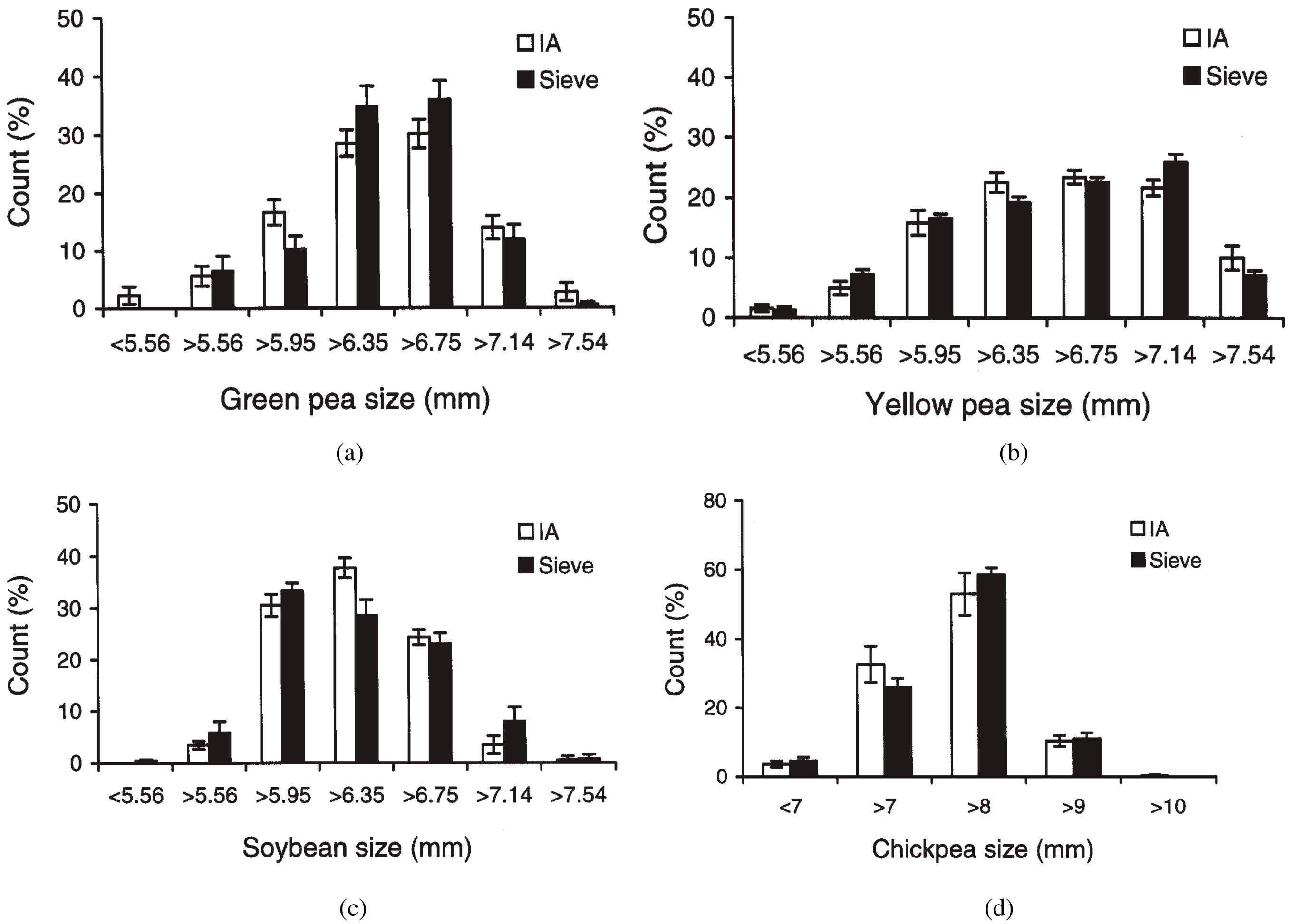

Fig. 3. Comparison of seed size distributions for: (a) green peas, (b) yellow peas, (c) soybeans, and (d) chickpeas.

operators differences were not significant for all the four commodities tested ($p > 0.15$ for operator and $p > 0.89$ for replicates). The probable differences in the two methods hinted by the ANOVA test in case of green and yellow peas are not surprising in light of the data in Table 1 that indicates overestimation for these two commodities as opposed to random errors for soybean and chickpea samples. Practically, the observed differences are small and have no serious ramifications. These differences can further be reduced by slightly adjusting the spatial calibration scale such that the mean differences are approximately zero. Imaging at higher resolution, say at 300 dpi instead of 100 dpi used here, may also help reduce these differences as this would minimize information loss experienced in seed boundary separation using morphological operations. Increasing the spatial resolution improves the clarity and sharpness of the seed features at the boundaries especially for the large seeds, which are typically moving out of focus of the scanner lens primarily designed for flat document scanning. However, imaging at higher resolution would increase the image size many folds requiring considerably longer processing time.

Sample-by-sample comparison of seed size distributions also indicated a close match between the two methods for all the four commodities tested. Figure 3 compares the size histograms from the two methods for one of the green peas, yellow peas, soybeans and chickpea samples, respectively. There are some minor deviations in the bar heights, however, these deviations for the most part are within one standard deviation error bars. Overall, the two methods produced similar distributions for each commodity. From the IA perspective, these deviations from the sieving results can be attributed to the still remaining lack of desired seed orientation for imaging and information loss in image processing. In the case of soybeans, however, these deviations may also be due to sampling error − no two sub-samples would share the exact same seeds in which case size measurements averaged over 2 or 3 images covering the entire sample in single layer are expected to compare better with the sieving results. Moreover, it should be noted that the sieving method itself is not perfect and free from errors. Sieving is problematic when the seed size is very close to the sieve hole size where, depending upon the procedure, seeds may or may not get caught in the sieve itself. Sieve manufacturing tolerances and the human factors associated with manual sieving can introduce errors in the sieving results. There is a manufacturing tolerance of approximately ±0.1 mm associated with sieve holes whereas the IA method uses fixed threshold values to create size bins. This factor alone could cause deviations in the height of the distribution bars obtained with the two methods. Moreover, it should be noted that size distribution with IA method is a two-dimensional (2D)

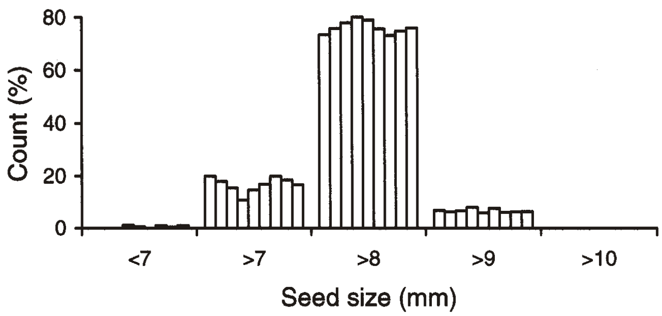

Fig. 4. Size distribution for repeated scans of a chickpea sample.

approximation to the 3D sieving process that can only be accurate for spherical objects. Despite all these difficulties, the IA method output closely matched the sieving results.

Figure 4 shows the seed size distributions obtained with the IA method for re-pours of one of the chickpea samples. The IA method consistently produced similar size histograms for sample re-pours over time demonstrating the robustness and repeatability of the method. The maximum deviation in the predominant size bins was within 6% except for one scan which differed by 9% from the others. A similar trend was observed for other commodities tested. These results were in accordance with the ANOVA test results showing statistical insignificance for the operator and replication effects. This shows that the IA system will produce consistent, reliable, and accurate size results over time. Moreover, the IA method allows for flexible user-defined size bins as opposed to fixed size bins in sieving. Due to this flexibility, the IA method allows for customized size distribution profiles for different customers, such as plant scientists or food processors, without having to have speciality sieves and performing the size analysis multiple times. This feature of the IA method can be very useful in food industry where the uniformity of grain seeds is one of the concerns for quality control, and may have more importance than mean size per se.

The results of this research indicate that the scanner based IA method can be used as an alternative method to sieving for sizing peas, soybeans, and chickpeas with minimal effect on accuracy in comparison with the sieving method. The IA method was faster than the sieving method. It took less than 30 seconds to scan and measure one sample while sieving a sample took about 12 minutes. Suitability of the proposed IA method for sizing more complex seed shapes such as kidney beans and cereal grains requires further testing which is planned as future work.

CONCLUSIONS

Measuring seed size from bulk images is possible as the seed boundaries can be separated through image processing. Thus, seed sizing is a strong candidate for automated image analysis. The following conclusions can be drawn based upon the results of this research:

1. The IA method can successfully measure seed size from non-singulated samples of various commodities differing in seed shape. Both the spherical (green peas, yellow peas) and non-spherical (soybeans, Kabuli chickpeas) seeds in the image can be separated through image processing for size measurements.
2. Results from the IA method closely match the sieving results in terms of the accuracy of measuring both the average seed size and size distribution for all the four commodities tested. The two methods are not statistically different ($p > 0.05$) with the maximum error less than 3% (1.2% on average). The IA method is highly repeatable and robust. There is no significant effect on the system output for different operators using the system ($p > 0.1$) as well as repeated scans of a sample ($p > 0.8$).

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