Quantification of variations in machine-vision-computed features of cereal grains

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*[1]Department of Biosystems Engineering, University of Manitoba, Winnipeg, Manitoba R3T 5V6, Canada; and [2]Cereal Research Centre, Agriculture and Agri-Food Canada, Winnipeg, Manitoba R3T 2M9, Canada. *Email: Digvir_Jayas@UManitoba.ca.*

Paliwal, J., Jayas, D.S., Visen, N.S. and White, N.D.G. 2005. **Quantification of variations in machine-vision-computed features of cereal grains.** Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **47**: 7.1-7.6. For machine-vision based identification and classification of cereal grains, the variability in features of grain kernels can occur due to the kernel orientation, different growing regions, and images acquired from different types of cameras. In an effort to quantify these variations in features, six morphological, nine color, and seven textural features were extracted from high-resolution images of five different cereal grains (barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye). Except for the width related morphological features of barley, there was little variation in extracted features of all the grain types when a kernel was randomly dropped several times in the field of view of the camera and imaged. Within the different kernels of a grain type, morphological features showed more variability than color or textural features. The variability in features due to different image acquisition devices was statistically insignificant. **Keywords:** digital image analysis, cereal grains, feature extraction.

La précision des procédés d'identification et de classification des grains de céréales par des systèmes de vision artificielle en termes de variabilité des caractéristiques des grains peut être affectée par l'orientation des grains, leur provenance géographique ainsi que par les images recueillies par différents types de caméras. De manière à quantifier ces variations, six caractéristiques morphologiques, neuf couleurs et sept caractéristiques de texture ont été extraites d'images à haute résolution de grains de cinq céréales différentes (orge, blé Canada Western Amber Durum (CWAD), blé Canada Western Red Spring (CWRS), avoine et seigle). À l'exception de la largeur reliée aux caractéristiques morphologiques des grains d'orge, il y avait peu de variation entre les caractéristiques obtenues pour tous les types de grains lorsque de manière aléatoire un grain tombait de manière répétée dans le champ de vision de la caméra et était photographié. Pour des grains différents d'un même type de céréale, les caractéristiques morphologiques ont montré plus de variabilité que la couleur ou les caractéristiques de texture. La variabilité des caractéristiques causée par les différents équipements de prise d'images n'était pas statistiquement significative. **Mots clés**: analyse d'image digitale, grains de céréales, caractéristique d'extraction.

INTRODUCTION

Most machine vision inspection systems rely on placing grain kernels in the field of view (FOV) of a camera and then extracting features from the acquired images. These features are then used for classification of the cereal grains. The kernels with closely packed features in the pattern space are said to belong to one specific output class. Thus, for correct classification of these biological entities we need repeatability in extracting these features.

Determining the potential of morphological features to classify different grain species, classes, varieties, damaged grains, and impurities using a statistical pattern recognition technique has been the main focus of the published research (e.g., Neuman et al. 1987; Keefe 1992; Paliwal et al. 1999; Majumdar and Jayas 2000a). A few studies have also been conducted to classify cereal grains using color features (Neuman et al. 1989a, 1989b; Luo et al. 1999; Majumdar and Jayas 2000b) and textural features (Majumdar et al. 1999; Majumdar and Jayas 2000c). These features, however, may vary for several reasons. Firstly, depending on its shape, any given kernel when placed in the FOV of the camera can lie in more than one orientation. Thus, a different set of morphological, color, and textural features will be calculated by the machine vision system depending on the orientation of the kernel. Secondly, the variation in features can arise due to different samples of the same grain type coming from different growing regions having different growing conditions. Thirdly, even after doing spatial and color calibration, images of a given object can have slight differences when acquired using different cameras under different illumination conditions due to optical characteristics of the camera lens. To implement the techniques of machine vision to automate the grain grading and handling processes, it is necessary to know the variability that may exist in the classification features. Therefore, the objectives of this research were to quantify the variations in morphological, color, and textural features of barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye:

- when the same kernel was dropped randomly in the FOV of the camera;
- when samples were acquired from different growing regions; and
- when the samples were imaged using an area- and a line-scan camera.

MATERIALS and METHODS

Image acquisition

Two different kinds of cameras were used for image acquisition purposes. The area-scan camera system consisted of a 3-chip

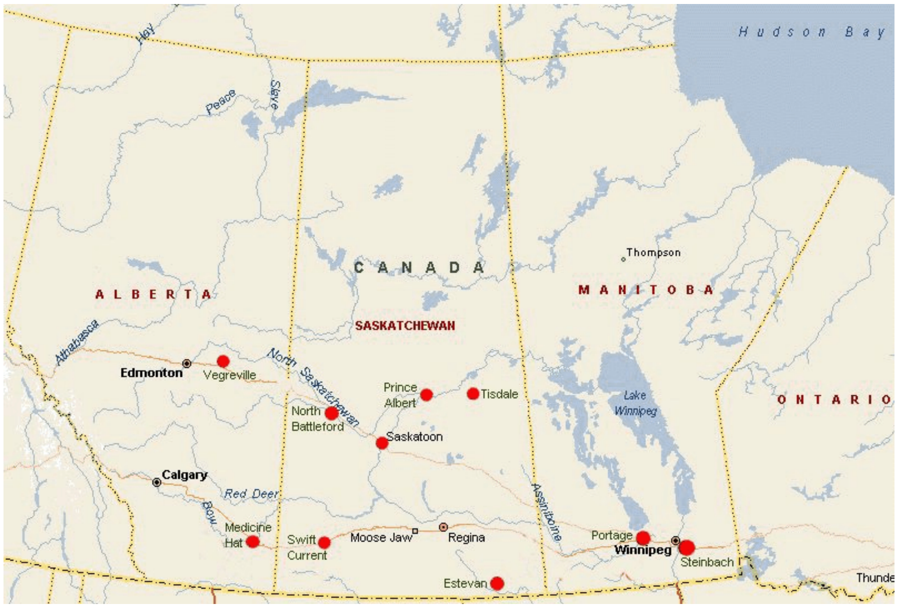

Fig. 1. Map of Canadian prairies indicating the growing regions from which the grain samples came.

CCD color camera (DXC-3000A, Sony, Tokyo, Japan) with a zoom lens of 10-120 mm focal length (VCL-1012BY), a camera control unit (CCU-M3, Sony, Tokyo, Japan), a personal computer (PC) (PIII 450 MHz), color frame grabbing board (Matrox Meteor-II multi-channel, Matrox Electronic Systems Ltd., Montreal, QC), and a diffuse illumination chamber. The camera captured images of objects in the illumination chamber. Illumination was provided by a fluorescent light source of 305 mm diameter, 32-W circular lamp (FC12T9/CW, Philips, Singapore) with a rated voltage of 120 V. The NTSC composite color signal from the camera was converted by the camera control unit at a speed of 30 frames per second into three parallel analog RGB video signals and a synchronous signal. The frame grabber installed in the PC digitized the RGB analog video signals from the camera control unit into three 8-bit 640 x 480 digital images and stored them in the hard disk of the computer as uncompressed tagged image file format (tiff) images. The line-scan assembly consisted of a conveyor belt system, line-scan camera (Model Trillium TR 2K, Dalsa, Waterloo, ON), power supply (PS3-DP9-115, Vision 1, Bozeman, MT), PC (PIII 450 MHz), color frame grabbing board (Model Viper-Digital, Coreco Inc., St. Laurent, QC), and a fluorescent light source. The camera was fitted with a macro lens (SP 90 mm, Tamron Inc., Commack, NY) of 90 mm focal length using a Canon FD mount adapter. The frame grabber board supplied control information to the camera and monitored the speed of the conveyor belt via the output from the rotary shaft encoder (M21AA, Dynamics Research Corporation, Andover, MA). The grain sample was poured into a hopper attached to the conveyor belt. It was imaged as it passed underneath the camera and the image files were saved in the tiff format.

Prior to starting image acquisition, both the cameras were calibrated for color and pixel spatial resolution. A Kodak white card with 90% reflectance (E152-7795, Eastman Kodak Co., Rochester, NY) was used as a white reference to standardize the illumination level. The image of the white card was acquired and over a small central area of 50 x 50 pixels the mean gray level values of the R, G, and B bands were computed and used as the illumination level indicators. By manually adjusting the iris control, all three values (R, G, and B) were adjusted to 250 ± 1. Spatial calibration was done by taking the image of a Canadian 10-cent coin, counting the number of pixels in its diameter, and then measuring it with a micrometer (No. 961, Moore and Wright, Sheffield, England). The spatial resolution of the images was 6.38 x 10^{-2} mm/pixel. After acquiring 50 images, color and spatial calibrations were done again.

Grain samples

The grain samples used in this study were collected from ten different growing locations throughout Western Canada (Fig. 1). The choice of locations was based on climatic subdivisions of the Canadian Prairies (Putnam and Putnam 1970). The selected locations represented two sample locations from the humid prairie (Portage and Steinbach); three locations from the sub-boreal region (Vegreville, Prince Albert, and Tisdale); three locations from the sub-humid prairie (North Battleford, Saskatoon, and Estevan); and two locations from the semi-arid region (Medicine Hat and Swift Current).

To obtain variability due to random orientation of kernels, one kernel of each grain type was taken and imaged by the area-scan camera by dropping it in the FOV of the camera. The same kernel was dropped 20 times to obtain the maximum number of possible orientations in which it could place itself in the FOV. For each grain type, 10 kernels were randomly selected and each one imaged 20 times by the area-scan camera. To quantify the variability in kernels due to different growing regions, 200 kernels from each of the ten growing regions were taken and imaged using the area-scan camera.

To compare the performance of the area- and line-scan camera systems, a kernel of a specific grain type was taken and positioned in the FOV of the area-scan camera system in a specific manner (crease up or down). The same kernel was then placed on the conveyor belt of the line-scan camera system in exactly similar fashion. Five hundred kernels (50 from each of the ten growing regions) of each grain type were imaged by both area- and line-scan camera systems and their morphological, color, and textural features were extracted and compared.

Feature extraction

The six morphological features extracted from the grain kernel images were area, perimeter, maximum radius, minimum radius, major axis length, and minor axis length (Majumdar and Jayas 2000a). For color features, the mean, variance, and range of the red (R), green (G), and blue (B) color primaries for each kernel were calculated and used as features. As textural features, gray level co-occurrence matrix (GLCM) and gray level run-length matrix (GLRM) models were computed for gray scale images. To reduce computational time, the 256 gray levels of images were reduced to 32 gray levels. A detailed description of the

Table 1. Maximum values of coefficient of variation (CV%) obtained for each grain type when features from a single kernel were extracted by randomly dropping it 20 times.

Features	Barley	CWAD	CWRS	Oats	Rye
Morphological					
Area	12.02	4.32	3.85	4.35	5.61
Perimeter	8.82	3.87	4.21	6.54	4.69
Maximum radius	7.54	4.34	3.99	5.41	4.78
Minimum radius	10.31	3.25	4.27	4.82	5.18
Major axis	6.24	5.28	6.11	5.27	6.22
Minor axis	11.64	6.16	5.15	6.43	5.34
Color					
Red mean	3.28	5.37	6.34	6.17	4.92
Red range	6.57	4.38	3.66	5.95	6.96
Red variance	6.65	3.29	5.54	3.50	5.29
Green mean	4.48	5.54	5.98	6.63	4.28
Green range	6.91	4.65	5.26	4.10	6.86
Green variance	3.23	6.19	4.38	4.86	6.22
Blue mean	6.36	5.20	3.92	6.02	3.45
Blue range	3.61	3.07	5.05	6.12	4.08
Blue variance	3.87	5.93	6.71	5.98	6.11
Textural*					
GLCM mean	2.30	3.88	4.57	3.11	3.45
GLCM variance	5.34	5.31	3.70	4.08	3.81
GLCM correlation	2.84	6.21	3.58	3.91	5.17
GLCM entropy	3.35	2.77	2.31	5.28	4.58
GLRM short rum	4.39	2.33	5.41	6.08	3.05
GLRM long run	5.30	2.37	2.54	5.23	4.63
GLRM run percent	4.78	3.82	5.12	4.54	4.27

* GLCM - Gray Level Co-occurrence Matrix
GLRM - Gray Level Run Length Matrix

GLCM and GLRM matrices is given by Majumdar and Jayas (2000c). Four GLCM features namely, mean, variance, correlation, and entropy and three GLRM features namely, short run, long run, and run percent were used for classification (Majumdar and Jayas 2000c).

RESULTS

Variability due to random orientations

The mean and coefficient of variation (CV) of all the morphological, color, and textural features were calculated for every kernel (which was dropped in the FOV of camera 20 times). Although for CWAD, CWRS, rye, and oats there was very little variation in features extracted from one given kernel when it was dropped randomly in the FOV of camera, barley stood out as an exception (Table 1). The variations in area, minimum radius, and minor axis length of barley were significantly different ($p<0.001$) when a given kernel was imaged in different orientations. This can be attributed to the awns and husk on the kernels of barley that allowed the kernels to position themselves in a variety of orientations. The variability in the length-related features (i.e., maximum radius and major axis length) was low because irrespective of the orientation of the kernel, the length is not affected much. The parameter that was affected the most by different orientations of the kernel was its width. Thus the width-related features (i.e., minimum radius and minor axis length) showed a higher CV.

When individual kernels were imaged in different orientations, the CVs of the color and textural features for all the grain types were very low (Table 1). This was because the color and textural parameters of kernels are generally uniform across their surface. When the kernels were dropped randomly, sometimes they landed with the crease-side up and sometimes with the crease-side down. This resulted in some amount of variation in the color and textural features as the color components and their distribution on the kernel surface were different on the crease and on the reverse side. However, these differences were not statistically significant at $p<0.01$.

Variability within different kernels of a grain type

To compare the variations among the corresponding extracted features within different kernels of a given grain type, a one-way analysis of variance (ANOVA) was done in SAS (SAS Institute, Cary, NC). The F values shown in Table 2 indicate that the variability in features for different grain types could be explained by the extracted features at $p<0.001$. A larger F value indicates a greater significance of the model explaining the variation in features due to different kernels. It is important to note that the significance of length related features (maximum radius and major axis length) is much higher than other features indicating the importance of the length of the kernel in characterizing its class. Similar analysis on color and textural features indicated no specific trend as these features showed little variability from kernel to kernel within a grain type (data not shown).

Table 2. F values indicating the significance of variation in morphological features among kernels of a given grain type ($p<0.001$).

Grain type	Area	Perimeter	Maximum radius	Minimum radius	Major axis	Minor axis
Barley	17.25	53.89	147.37	18.56	151.08	21.83
CWAD	196.25	226.79	827.16	26.06	1449.26	32.74
CWRS	207.37	118.81	231.33	51.50	430.91	68.79
Oats	442.01	130.28	482.36	55.34	550.09	130.90
Rye	306.80	53.17	686.04	12.56	1688.22	21.28

Table 3. F values indicating the significance of variation in morphological features among kernels of different grain types coming from various growing regions (p<0.001).

Grain type	Area	Perimeter	Maximum radius	Minimum radius	Major axis	Minor axis
Barley	1258.64	623.45	785.91	499.51	875.64	583.46
CWAD	987.24	585.33	628.13	650.28	762.46	627.38
CWRS	894.21	419.39	468.82	526.32	731.68	467.29
Oats	1121.84	590.85	613.91	642.26	867.35	459.85
Rye	1082.67	742.00	407.33	523.34	792.87	616.45

Table 4. F values indicating the significance of variation in color features among kernels of different grain types coming from various growing regions (p<0.001).

Grain type	Red mean	Red range	Red variance	Green mean	Green range	Green variance	Blue mean	Blue range	Blue variance
Barley	732.5	978.4	763.6	930.8	681.9	745.4	936.6	887.2	838.0
CWAD	843.3	915.4	999.1	637.3	1167.7	959.0	811.6	613.4	665.9
CWRS	1049.1	870.0	1072.1	813.5	740.1	949.1	1244.2	736.8	1081.2
Oats	816.3	716.0	739.8	749.2	629.0	669.8	963.3	692.8	875.1
Rye	979.7	601.7	625.7	866.8	875.8	814.3	855.4	882.3	601.7

Table 5. F values indicating the significance of variation in textural features among kernels of different grain types coming from various growing regions (p<0.001).

Grain type	GLCM* mean	GLCM variance	GLCM correlation	GLCM entropy	GLRM# short run	GLRM long run	GLRM run percent
Barley	363.57	491.43	382.17	393.09	493.96	402.55	448.50
CWAD	439.71	491.19	467.39	506.16	542.62	496.13	485.58
CWRS	491.12	445.34	356.83	542.36	435.55	376.89	353.07
Oats	534.01	408.05	548.43	447.32	539.21	389.36	368.31
Rye	466.97	509.60	576.15	534.25	485.50	431.37	501.15

* GLCM - Gray Level Co-occurrence Matrix
\# GLRM - Gray Level Run Length Matrix

Variability due to growing region

Analysis of variance was done to see the effect of various growing regions on the morphological, color, and textural features. The F values in Tables 3, 4, and 5 indicate the significance of growing regions on almost all the features at p<0.001. Among the morphological features (Table 3), the maximum variation is in the area of kernels. Kernels coming from different growing regions may vary in size (both length and width). So the area of the kernel, which is a consequence of size, gets affected the most. It is very difficult to point out which grain type showed the maximum variability in shape and size. Color showed the highest variability for kernels coming from different growing regions (Table 4). This is because of all the visual characteristics, color varies the most for samples of the same grain type coming from different regions. The variability in texture was less than that of morphological and color features (Table 5).

Variability due to different imaging systems

The morphological, color, and textural features of kernels of each grain type were extracted and compared. The means and CVs of the features are shown in Tables 6, 7, and 8. A t-test indicated that the values of all the corresponding morphological features and most of the color and textural features obtained using the area-scan and line-scan cameras were statistically similar (p<0.01). The difference in some of the color and textural feature values can be attributed to the different illumination sources used for the two cameras. Although the cameras were calibrated for color, the stability of illumination over time might not have been similar and could have caused the variation in color and texture. Nevertheless, the similarity in the majority of the feature values leads us to conclude that if the spatial and color calibration is done properly, comparable images can be acquired using different imaging systems.

CONCLUSIONS

The orientation in which a kernel falls in the field of view (FOV) of the imaging system, the growing region from where a grain sample may come, and the image acquisition system being used in a study, can cause variations in features that are extracted by a machine vision system. The orientation of the kernel can affect the width related features in grains with awns and husk such as barley. Within a grain type, the kernels show more variation in morphology than color or texture. This can be

Table 6. Mean and coefficient of variation (%) of the morphological features for different grain types when the kernels of a particular growing region were imaged using an area-scan camera (ASC) and a line-scan camera (LSC).

	Camera	Barley	CWAD	CWRS	Oats	Rye
Area	ASC	21.7 (10.1)*	17.8 (10.7)	14.5 (8.8)	27.2 (5.9)	15.8 (8.7)
(mm^2)	LSC	21.6 (9.8)	17.8 (11.6)	14.2 (8.0)	27.1 (6.7)	16.2 (9.2)
Perimeter	ASC	21.6 (7.6)	18.3 (6.8)	16.0 (4.9)	27.3 (4.7)	18.4 (6.7)
(mm)	LSC	21.6 (7.2)	18.2 (6.0)	15.9 (4.3)	26.8 (5.2)	18.5 (5.6)
Maximum radius	ASC	4.5 (7.2)	3.7 (7.9)	3.2 (6.8)	5.2 (4.7)	4.0 (7.2)
(mm)	LSC	4.5 (7.0)	3.8 (8.1)	3.1 (5.8)	5.1 (5.1)	4.2 (6.6)
Minimum radius	ASC	1.4 (8.6)	1.4 (9.4)	1.5 (8.6)	1.3 (4.3)	1.2 (7.4)
(mm)	LSC	1.5 (8.8)	1.3 (8.6)	1.4 (8.1)	1.2 (3.8)	1.2 (8.0)
Major axis	ASC	8.5 (7.3)	7.3 (7.2)	6.2 (5.8)	9.9 (6.4)	7.4 (5.6)
(mm)	LSC	8.4 (6.9)	7.5 (7.6)	6.3 (5.1)	10.2 (6.2)	7.5 (6.5)
Minor axis	ASC	3.3 (8.2)	3.1 (9.0)	3.1 (8.3)	2.7 (5.0)	2.8 (7.0)
(mm)	LSC	3.4 (8.0)	3.0 (9.8)	3.0 (7.1)	2.6 (5.7)	2.8 (7.6)

* Values in parenthesis indicate the coefficient of variation (%) based on n=500.

Table 7. Mean and coefficient of variation (%) of the color features for different grain types when the kernels of a particular growing region were imaged using an area-scan camera (ASC) and a line-scan camera (LSC).

	Camera	Barley	CWAD	CWRS	Oats	Rye
Red mean	ASC	112.1 (8.6)*	99.9 (7.6)	108.4 (11.5)	108.4 (10.4)	116.1 (4.5)
	LSC	123.4 (10.3)	108.4 (5.9)	98.0 (10.0)	118.1 (12.1)	108.2 (5.6)
Red range	ASC	127.5 (9.8)	105.6 (11.8)	106.5 (10.5)	125.4 (11.0)	121.5 (11.8)
	LSC	122.0 (11.0)	123.0 (11.2)	120.4 (11.8)	132.9 (9.8)	126.4 (10.5)
Red variance	ASC	322.1 (7.6)	276.5 (9.5)	431.5 (7.7)	288.2 (7.3)	341.3 (10.5)
	LSC	308.9 (7.4)	300.4 (9.3)	436.8 (8.0)	268.7 (7.5)	333.4 (9.4)
Green mean	ASC	96.8 (10.1)	98.7 (10.3)	85.8 (9.4)	96.2 (8.7)	101.6 (9.8)
	LSC	103.6 (8.5)	91.3 (10.2)	91.2 (7.5)	96.5 (7.0)	96.0 (8.5)
Green range	ASC	171.2 (6.3)	140.5 (8.5)	155.4 (6.2)	165.9 (12.4)	133.1 (10.0)
	LSC	165.9 (5.7)	156.8 (7.9)	160.1 (6.6)	158. 1 (11.2)	123.4 (9.8)
Green variance	ASC	640.8 (7.6)	642.1 (6.6)	686.9 (9.4)	490.0 (7.4)	596.8 (10.3)
	LSC	671.6 (6.2)	626.7 (6.1)	701.4 (8.1)	468.1 (6.4)	615.0 (11.4)
Blue mean	ASC	48.9 (8.7)	28.7 (8.5)	36.4 (11.0)	48.6 (8.1)	38.4 (8.5)
	LSC	42.0 (6.5)	29.6 (9.2)	35.1 (12.8)	50.4 (8.2)	36.9 (10.2)
Blue range	ASC	96.7 (9.0)	116.4 (6.4)	133.0 (5.9)	108.4 (12.1)	121.6 (4.6)
	LSC	101.4 (7.9)	104.7 (7.0)	138.7 (6.2)	126.8 (11.6)	122.4 (4.0)
Blue variance	ASC	517.8 (10.4)	404.5 (10.3)	587.8 (7.8)	493.3 (6.6)	518.4 (8.6)
	LSC	496.6 (8.8)	389.8 (10.0)	606.9 (8.6)	453.1 (5.8)	508.7 (8.6)

* Values in parenthesis indicate the coefficient of variation (%) based on n=500.

attributed to the fact that kernels of grain coming from a very pure sample show little variation in color or texture but their sizes may differ significantly. While imaging the same kernel with different imaging systems, variability in color and textural features can appear. It is speculated that this variability arises due to manner and type of illumination associated with different imaging systems. Such variability can be minimized if spatial and color calibrations are done properly.

Table 8. Mean and coefficient of variation (%) of the textural features for different grain types when the kernels of a particular growing region were imaged using an area-scan camera (ASC) and a line-scan camera (LSC).

	Camera	Barley	CWAD	CWRS	Oats	Rye
GLCM* mean	ASC	113.06 (9.5)**	113.5 (9.5)	111.1 (8.1)	99.96 (6.4)	93.64 (7.8)
	LSC	98.49 (8.8)	121.4 (8.5)	104.8 (9.2)	97.45 (5.8)	94.52 (8.4)
GLCM variance	ASC	70265.41 (8.4)	67894.10 (7.4)	74268.91 (5.6)	65165.56 (7.1)	64819.08 (9.4)
	LSC	68652.07 (7.5)	66804.37 (8.0)	71579.07 (4.7)	61678.09 (6.6)	63870.64 (9.0)
GLCM correlation	ASC	0.98 (5.3)	0.96 (4.6)	0.99 (6.3)	0.99 (5.1)	0.98 (5.8)
	LSC	0.99 (4.8)	0.97 (5.2)	0.99 (5.1)	0.99 (3.8)	0.98 (6.0)
GLCM entropy	ASC	-12.84 (9.4)	-11.43 (6.7)	-12.31 (8.6)	-9.41 (5.2)	-14.80 (5.3)
	LSC	-12.35 (7.8)	-11.04 (7.3)	-11.88 (7.5)	-9.23 (5.0)	-17.58 (5.9)
GLRM# short run	ASC	0.28 (5.5)	0.22 (11.2)	0.24 (8.0)	0.22 (7.4)	0.23 (4.7)
	LSC	0.23 (5.5)	0.20 (11.1)	0.25 (6.8)	0.21 (6.5)	0.23 (5.6)
GLRM long run	ASC	2.04 (10.2)	3.47 (5.9)	2.16 (11.2)	3.07 (5.4)	1.50 (9.0)
	LSC	2.12 (9.7)	3.45 (5.7)	1.99 (10.5)	2.79 (5.6)	1.48 (9.3)
GLRM run percent	ASC	1.76 (3.6)	1.19 (9.1)	1.56 (5.1)	1.29 (5.7)	1.75 (8.2)
	LSC	1.69 (3.8)	1.22 (8.8)	1.54 (4.8)	1.29 (5.0)	1.69 (6.9)

* GLCM - Gray Level Co-occurrence Matrix
\# GLRM - Gray Level Run Length Matrix
** Values in parenthesis indicate the coefficient of variation (%) based on n=500.

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