

HIGH-SPEED SORTING OF GRAINS BY COLOR AND SURFACE TEXTURE

T. Pearson

ABSTRACT. *A high-speed, low-cost, image-based sorting device was developed to detect and separate grains with different colors/textures. The device directly combines a complementary metal-oxide-semiconductor (CMOS) color image sensor with a field-programmable gate array (FPGA) that was programmed to execute image processing in real-time without the need for an external computer. The spatial resolution of the imaging system is approximately 16 pixels/mm. The system utilizes the inherent parallel processing capabilities of FPGA's to inspect three separate streams of grain with a single camera/FPGA combination. Kernels are imaged immediately after dropping off the end of a chute and are diverted by activating an air valve. The system has a throughput rate of approximately 225 kernels/s overall, which is much higher than previously developed image inspection systems. This throughput rate corresponds to an inspection rate of approximately 25 kg/h of wheat. Testing of the system resulted in accuracies of 96% for separating red wheat from white wheat, 93% accuracy for separating barley from durum, and 92% for separating brown flax from yellow flax. The sorter should find use in removing other defects found in grain, such as scab-damaged and bunted wheat. Parts for the system cost less than \$2,000, so it may be economical to run several systems in parallel to keep up with processing plant rates.*

Keywords. *FPGA, CMOS, Machine vision.*

Automated separation of grains based on color and surface texture is needed by breeders, seed foundations, and seed companies to help purify lots. Commercial color sorters can distinguish many defects or undesirable seeds, but they lack accuracy in many other applications. Additionally, the cost of these sorters is high. Commercial sorters have been shown to separate red and white wheat with approximately 80% accuracy after several passes through the sorter (Pasikatan and Dowell, 2003), which may not always be accurate enough for some breeding lines with small amounts of white wheat. The only image processing performed by most commercial color sorters is thresholding and pixel counting. Consequently, for many products, certain defects are difficult to detect and remove. Shriveled and *Fusarium* head blight (scab-damaged) wheat kernels are a case in point. The efficacy of using a limited spatial resolution (~0.5 mm) commercial dual-band (one near infrared (NIR), one visible) sorter for removal of scab-damaged kernels has been studied (Delwiche et al., 2005). Only 50% of the scab-damaged kernels were removed, while about 5% of the undamaged kernels were also rejected.

Pearson (2009) developed an image-based sorter for separating red and white wheat that was highly accurate (>95%), but had a throughput of only ~2 kg/h. This system

utilized a personal computer to perform image processing and classification. Although the throughput of this machine is somewhat low, this device has found widespread use with many wheat breeders throughout the country. Nevertheless, requests for higher throughput with comparable accuracy have been repeated by breeders and foundation seed programs so that later breeding lines that might comprise several bushels of seed can be accurately sorted.

Field-programmable gate arrays (FPGA) are semiconductor devices comprised of interconnected logic elements (comprising a 4-input lookup table and a flip-flop), memory, and digital signal processing hardware on a single chip. The configuration of the interconnections, and therefore the function of the device, is determined by compiled programs loaded onto the chip. FPGA's are currently used in a large variety of applications where low cost and high data throughput rates are required, such as digital cameras, cell phones, speech recognition, and image processing (Maxfield, 2004). The advantages of FPGA's over micro-controllers and personal computers for image processing functions are that they can perform many computations in parallel and that they execute all commands in hardware, making them ideal for real-time systems. Additionally, FPGA's are able to perform computations on as they are transferred to the device and before the complete image has been loaded, reducing delay in classification.

Pearson (2009) developed a FPGA/image sensor combination and implemented a sorting system for grains. That system used three FPGA/image sensors placed around the perimeter of grain falling off the end of a chute so that the entire surface of the grain could be inspected. While this system had a throughput rate of 75 kernels/s, it was hypothesized that a similar system could be built that took advantage of an FPGA's ability to perform parallel processing and could inspect more than one stream of grain at a time with a single FPGA/image sensor combination. The

Submitted for review in October 2009 as manuscript number IET 8264; approved for publication by the Information & Electrical Technologies Division of ASABE in February 2010.

Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the U.S. Department of Agriculture.

The author is **Tom Pearson, ASABE Member Engineer**, Agricultural Engineer, USDA-ARS-CGAHR, 1515 College Ave, Manhattan, Kansas 66502; phone: 785-776-2729; fax: 785-537-5550; e-mail: thomas.pearson@ars.usda.gov.

purpose of this research was to develop a multichannel sorter that used one FPGA/image sensor to inspect three channels (chutes) of grain, improve on the previous systems' accuracy for sorting red and white wheat, and test it on other types of seeds. The system was tested for its ability to separate red wheat from white wheat, barley from durum, and brown from yellow flax seeds.

MATERIALS AND METHODS

IMAGE SENSOR – FPGA DESIGN

The image sensor/FPGA combination used for this device is very similar to that described in Pearson (2009), so only a brief overview will be given here. A CMOS image sensor (KAC-9628, Eastman Kodak Company, Rochester, N.Y.) was mounted onto a custom-designed printed circuit board with all support electronics for the image sensor recommended by the manufacturer. The FPGA, with its necessary support electronics, was purchased pre-mounted onto its own circuit board (Pluto-III, KNJN-LLC-fpga4fun.com, Fremont, Calif.). This FPGA board has more logic elements and memory than the one used in Pearson (2009). The free Altera Quartus II web edition version 7.2 was used to develop and compile programs for the FPGA. A C-mount lens mounting block was fabricated out of delrin and fastened to the image circuit board. A 25-mm lens (M2514-MP, Computar, Japan) was used.

The FPGA circuit board has a 25-MHz clock that was wired to the main clock input of the image sensor, so the pixel clock rate was 12.5 MHz. One image frame was limited to just two lines in the center of the image sensor. This essentially made the two-dimensional sensor work as a color linescan sensor. The image sensor used has either a red, green, or blue color filter over every pixel arranged in a Bayer pattern, typical of most two-dimensional image sensors. One

line consists of red and green pixels and the next line consists of green and blue pixels. Most two-dimensional color images are constructed by interpolating the colored pixels so that each pixel would appear to have a red, green, and blue value. However, this was not done in this application in order to reduce computations. Thus, the red and blue image data was one-quarter the full scale pixel resolution and the green image data was one-half the full scale raw pixel resolution. The analog image gain was set to a level of 128, which is the middle of the amplification range on this sensor. The 12.5-MHz clock rate produced images of grain kernels of the correct aspect ratio when the imaged lines were reconstructed to form a two-dimensional image.

SORTING SYSTEM PROTOTYPE

Figure 1 displays an image of the complete sorting machine prototype while figure 2 displays detail of the camera, chute, eject nozzle, and LED illumination. Kernels were fed in a single layer by a vibratory feeder (F-TO-C, FMC-Syntron, Homer City, Pa.) with a flat-bottom trough, 40 mm wide that was supplied with the feeder. The kernels dropped off the end of the feeder onto a chute with three parallel “vee” grooves. The chute was fabricated from aluminum bar stock with the three grooves machined into it. Each groove was 8 mm deep and spaced 12.7 mm apart. These grooves were close enough that kernels would singulate on them without overflowing or spilling off.

Image capture from the separate vee channels was accomplished by defining three regions of interest that corresponded with each vee groove. While the image sensor constantly scanned and output images, triggering and image analysis from the three regions of interest were processed separately on the FPGA using three different blocks of logic. While the three channels were captured by one image sensor

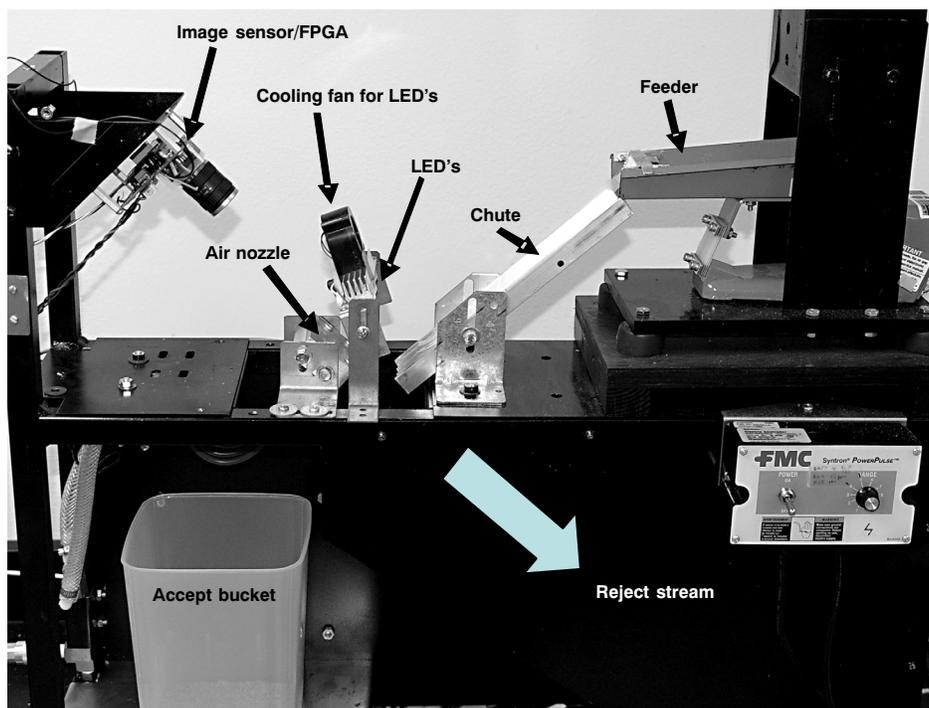


Figure 1. Photo of sorting system showing the cameras, illumination, eject nozzle, chute, and feeder.

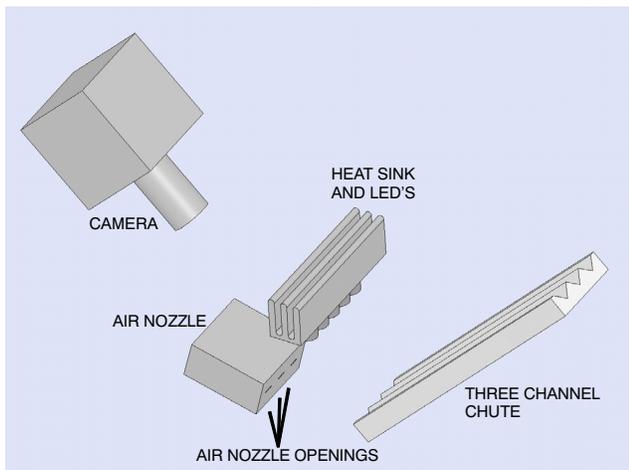


Figure 2. Schematic of sorter system showing detail of the arrangement of camera, illumination, eject nozzle, and chute.

and processed on FPGA, the image data for each channel was processed independently in three separate regions within the FPGA. This allowed for independent image capture and processing of the kernels coming off the three different vee grooves.

For diverting product, the FPGA outputs a digital signal which triggers one of three solid state relays (D0061B, Crydom, San Diego, Calif.) and fires an electronic, solenoid-activated air valve (36A-AAA-JDBA-1BA, Mac Valves, Inc., Wixom, Mich.). The air valve sends a burst of air for 3 milliseconds to an air nozzle that diverts the seed into the appropriate channel. The air nozzle was constructed from an aluminum block with three 1- × 10-mm slots spaced 12.5 mm apart machined into it. Air from the solenoid valve was plumed into the aluminum block and the nozzle positioned so one slot was opposite of each vee groove in the feeding chute. Any one, two, or three air nozzles could be activated without effecting grain kernels in an adjacent vee groove.

Illumination for each channel was provided by high power, white light emitting diodes (LED) (W42180U, Seoul Semiconductor, Korea). One LED was placed directly above each of the three channels, and one extra was placed on each end so that the center channel would not receive more light from adjacent LED's than the two edge channels. Each LED was coupled to a spot lens (OP005, Dialight, Farmingdale, N.J.) that focused the light onto a spot approximately 5 mm in diameter. A custom circuit board was fabricated to mount and power the LED's. The LED circuit board included a 0.5-mm diameter hole (same diameter as the LED) directly under each LED. A copper round of the same diameter was pressed into each hole to help conduct heat away from the LED. An aluminum heat exchanger was then mounted on the opposite side of the circuit board from the LED's. Finally, air was forced over the heat exchanger fins by means of a small fan (#BM5125-04W-B50-L00, NMB Technologies Corp., Chatsworth, Calif.). These LEDs had a maximum forward current of 1,000 mA, which was provided by a constant current source LED driver (TLD1040-36-C1050, Triad Magnetics, Corona, Calif.). All five LEDs were powered in series by a single current source so that they all received exactly the same amount of current. This helped to keep their light emission intensities uniform across all three channels.

Light output from each LED was measured by placing a 2.0 optical density neutral density filter (NT63-413, Edmund Optics, Barrington, N.J.) between the each LED lens and a small light meter (#615, B&K Precision, Yorba Linda, Calif.). Light output from the five LED's averaged 154 lm with a range of 150 to 162, a spread of 7.7% of the average.

The lighting was further equalized by dropping a laboratory grade 3.2-mm diameter white Teflon ball (9660K13, McMaster-Carr, Chicago, Ill.) down each channel 30 times. The FPGA would process the image of the ball and export the maximum and minimum green intensity values to a computer. The average maximum and minimum values for all balls dropped down each channel and was then computed and compared to the center channel. All of the minimum values of the ball region of the image were the same (33). While average maximums for all channels were within 7% of each other (ranging from 215 to 237), lookup tables were created for the two side channels so that their maximum and minimum intensities would be the same as the center channel. All further processing of kernels on the side channels was then performed on the intensity stretched image rather than on the raw image so that their intensity values would be very similar to intensity values from the center channel.

SIGNAL PROCESSING

Pearson et al. (2008) showed that the standard deviation of pixel intensities; the average pixel intensities of the red, green, and blue channels; and the number of pixels below a set threshold are good features for distinguishing red wheat from white wheat when using color images. Red wheat tends to have higher standard deviations of pixel intensities as they tend to have darker areas accompanied by lighter, almost white, areas at the beard end. Also, weathering tends to create light areas on red wheat kernels. The combination of darker red and lighter white areas drives the pixel intensity standard deviation higher than more consistently colored white kernels. Red wheat also has higher counts of blue pixels with dark intensity levels. This is due to the red kernel pigment absorbing blue light.

The FPGA was programmed to compute the variance of the red pixel intensities, the average pixel intensities of the red, green, and blue channels, and the cumulative histograms of the red, green, and blue color channels. Additionally, the sorter was programmed to compute a histogram of the slopes of the green pixels with a two-pixel gap in the horizontal direction only. This histogram, along with the variance of pixel intensities, can be used to characterize the texture of some kernels. All four of the computed histograms contained 16 bins. The color histograms spanned the range between intensity levels 16 through 255 while the slope histogram spanned from 0 to 30. Only absolute values of slope were used. The variance of the red pixels was computed by keeping a running tally of the sum and sum squared of the red pixel intensities above a threshold level of 15, which segmented the kernel from the background. After image capture was completed, the variance was computed using the pixel intensity average and sum squared.

Classification of kernels was based on a subset of three of the features using linear discriminant analysis. During training, the FPGA stored all computed image features in memory for each kernel in the center channel. After each kernel passed the camera, the data was exported out through

a serial port created on the FPGA to a PC where it was saved. The computer then processed the data to select the best three features and develop a discriminant function used to classify kernels, per Pearson et al. (2008). After the three features and discriminant function were computed, their parameters were written to a text file that the FPGA compiler read while compiling a new FPGA program for a particular application. After compilation, the new program was loaded onto the FPGA's non-volatile memory that was read during power up. So, for sorting, no external computer was needed to be connected to the FPGA/image sensor system.

A 16-position rotary DIP switch on the FPGA was used to adjust the threshold probability (and therefore move the decision boundary) for classifying kernels. This enabled a user to adjust the sensitivity of the system to bias it toward more aggressive or conservative diversion of desired product.

SAMPLE SOURCE AND SORTER TESTING

The red and white wheat were of the Jagger and Betty varieties, respectively (shown in fig. 3). Barley was of the "Tradition" variety supplied from the North Dakota Seed Foundation. The durum was collected from a grain elevator in Northern Minnesota and was of unknown variety. It probably consisted of a mixture of several varieties, and some were vitreous while others were a more chalky yellow color. Representative samples of barley and durum are shown in figure 4. The brown and yellow flax seed (shown in fig. 5) were also of unknown varieties but originated in North Dakota.

The sorter was trained using pure samples of the two types of seeds desired to be sorted using the procedure outlined in the previous section. Each training session took about 10 min. The sorter was trained to separate white wheat from red



Figure 3. White wheat (left) and red wheat (right) used in this study.



Figure 4. Barley (left) and durum (right) used in this study.



Figure 5. Brown flax (left) and yellow flax (right) used in this study.

wheat, barley from durum, and brown from yellow flax. Approximately 1800 g of red wheat, durum, or yellow flax were added to 200 g of white wheat, barley, and brown flax, respectively, to form mixtures of the seeds for sorter testing. After training the sorter for each application, the seeds were sorted and the accuracy of the sorted lots estimated by visually inspecting 50 g sub-samples of the accept and reject streams. Each mixture was sorted and inspected 10 times every two days for 12 days to determine if accuracy degraded over time. However, the sorter was trained for each application only at the beginning of the 12-day test.

RESULTS

All results are tabulated in table 1 and discussed separately in subsections for each commodity studied.

RED AND WHITE WHEAT

The average accuracy achieved by the system was 98.6% for red wheat and 93% for white wheat during the 12-day period. Analysis of variance did not find any significant ($p = 0.05$) change in accuracy over time during the 12-day testing period (fig. 6). These accuracies are more than 10% to 20% above what can be accomplished after passing wheat through a commercial color sorter several times (Pasikatan and Dowell, 2003). Additionally, these accuracies are comparable to what has been accomplished using three similar features extracted from color images using a traditional camera and personal computer to do the image processing (Pearson et al., 2008). However, this FPGA system has 10 times greater product throughput and is likely to be more physically robust, since a PC is not required during sorting (and only temporarily required for training). Note that in figure 6, there is some fluctuation in accuracy from day to day. Some of the fluctuation might be contributed by human error in visually distinguishing red and white kernels. It appears that a small rise in red wheat accuracy coincides with a small drop for white wheat, and vice-versa. The standard deviations in accuracy for all tests were 0.75% for both red and white wheat. All of the average accuracies for each day are within two standard deviations of each other.

The feature selection process during training selected the average green, average red, and the number of pixels corresponding to a moderately high slope of 25. Red wheat had lower values of average green and red, and higher values of pixels having a moderate slope. This is likely due to transitions from darker red regions to lighter regions on the kernel where the beard is.

Table 1. Summary of sorting result tests for the 12 day test period.

Grains sorted	Specific Grain	Average Accuracy over 12-Day Test (%)	Standard Deviation over 12-Day Test (%)	Image Features Used
Red vs. white wheat	Red wheat	98.6	0.70	Average green, average red, number of pixels corresponding to a slope of 25
	White wheat	93.0	0.65	
Barley vs. durum	Barley	93.0	0.55	Average green, count of blue pixels below intensity of 60 and the number of pixels having a slope of 10
	Durum	93.0	0.60	
Yellow vs. brown flax	Yellow flax	94.0	0.50	Average red, green, and blue values
	Brown flax	90.0	0.40	

BARLEY AND DURUM

Average accuracy for both barley and durum was 93% during the 12-day testing period (standard deviation = 0.60 for durum and 0.55 for barley). The accuracy of distinguishing barley and durum was overall about 3% less than for red and white wheat. However, the color difference, surface texture, and shape of the kernels were somewhat easier for humans to distinguish than red and white wheat. Durum was generally darker and smaller than barley, but kernels that were mottled had larger regions that were lighter than barley kernels. Still, humans can distinguish these kernels based on shape and surface texture. Majumdar and Jayas (2000a) developed image processing and classification schemes using color information only to discriminate durum from barley. This study was performed with digital images of stationary seeds and resulting accuracy was 92% for durum and 93% for barley. Even though this study did include a wide variety of samples, their results are very close to what is accomplished here where seeds are imaged while in freefall. Later, Majumdar and Jayas (2000b) combined color information with morphological features from digital images to improve accuracies for distinguishing durum from barley to over 99%. Incorporating kernel morphological features into the FPGA program will be the focus of future research.

The training process selected the average green, a cumulative histogram bin from the blue pixels at an intensity of 60, and the number of pixels having a low slope of 10 as features for classification. Durum had lower average green values, higher counts of darker blue pixels below a level of 60, and lower counts of pixels with a low slope. The rough

texture of the barley likely caused the counts of pixels with a low slope to be higher than durum. Durum kernels that were mottled had higher counts of pixels with moderate slopes but the darker and lighter regions of these kernels are consistent and have many adjacent green pixels with zero or small slopes between them.

The average accuracy values for durum and barley did not fluctuate as much as red and white wheat did (fig. 7), and this is reflected in a slightly smaller overall standard deviation in accuracy values for all of the tests. The lower fluctuation in accuracy values from day to day may be due to less human error in distinguishing these kernels.

BROWN AND YELLOW FLAX

Average accuracy was 90% for brown flax and 94% for yellow flax during the 12-day period. The standard deviations for yellow and brown flax were 0.5 and 0.4, respectively, for all tests over the 12-day period. Even though yellow and brown flax seed was the easiest to distinguish with the human eye, the accuracy for these seeds was the lowest of the three sets studied. The small size of flax probably contributed to this. Also, the shape of flax seeds was problematic as they are very thin and sometimes only their edge is presented to the camera. This tends to make yellow flax seeds appear darker. Finally, there may also be more errors made when flax seeds are rejected due to their small size.

The features selected to discriminate brown and yellow flax were the average red, green, and blue values. The flax seeds tend to have very consistent color over their entire

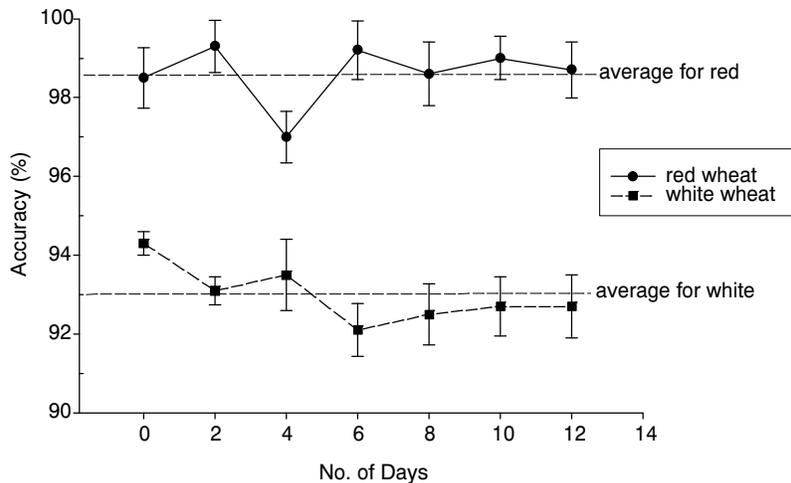


Figure 6. Average accuracies for each day of testing with the sorting system running red and white hard winter wheat.

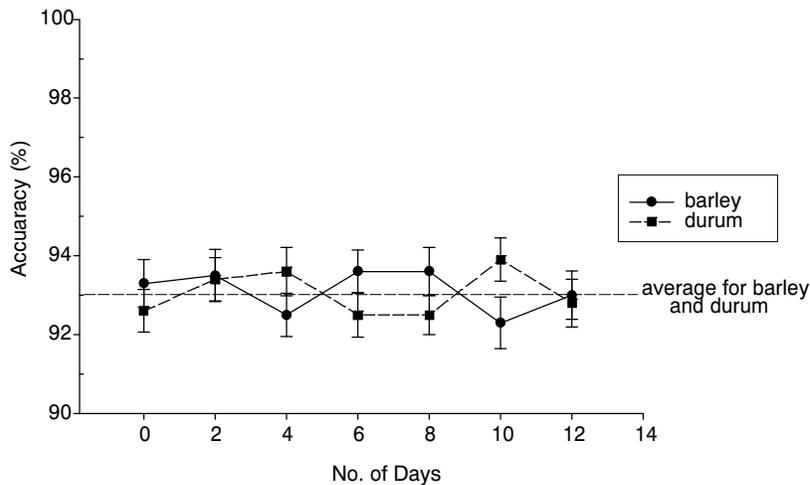


Figure 7. Average sorting accuracies for each day of testing of the sorting system running barley and durum.

surface and the brown and yellow seeds are both very smooth and of the same surface texture. The average values of red, green, and blue pixel values are not as affected by the size of the seed, which helps mitigate effects of seed orientation when imaged. However, the seed orientation may affect how light is reflected from it, which has an effect on the overall lightness in the resulting image. More lights than one row of LED's may help reduce the effect of seed orientation on flax seeds.

Like the sorting tests with barley and durum, accuracy of flax sorting did not fluctuate as much as the red and white wheat did during the 12-day testing period (fig. 8). The standard deviations were similar to barley and durum, and no average for each day was separated by more than two standard deviations from any other point. As shown in figure 8, there does not appear to be a downward trend in sorting accuracies over the 12-day testing period.

DISCUSSION

GENERAL DISCUSSION

The combined throughput of 225 kernels/s approximates that of high-speed commercial color sorters and is substantially higher than what has been developed so far

using traditional cameras connected to personal computers that perform the image processing (Pearson et al., 2008). Traditional cameras may output images of similar resolution at rates of 60 frames per second, but inspection rates are about half (30 kernels/s) due to kernel feeding limitations. The image sensor/FPGA combination has much less latency in data transmission than a camera connected to a PC does, so the kernels can be spaced much closer to one another. Parts costs for this three channel FPG-based system are actually slightly less than the PC-based system (Pearson et al., 2008) and are about \$2000.

Higher accuracy for some seeds might be achieved if the FPGA were programmed to extract shape features such as length, width, length/width, perimeter, and/or Fourier descriptors (Gahzanfari et al., 1997; Majumdar and Jayas, 2000b). Better color accuracy might be achieved if the FPGA were programmed to change the color coordinates to hue, saturation, and lightness where hue and saturation define color without effects of overall brightness. This will be the focus of future research. The FPGA used in this study has 4,608 logic elements, and approximately 3,000 are used to compute the features that are currently extracted. Other FPGA's with many more logic elements are readily available. Nevertheless, the sorter accuracies for the three applications presented here are more than adequate for the device to be a

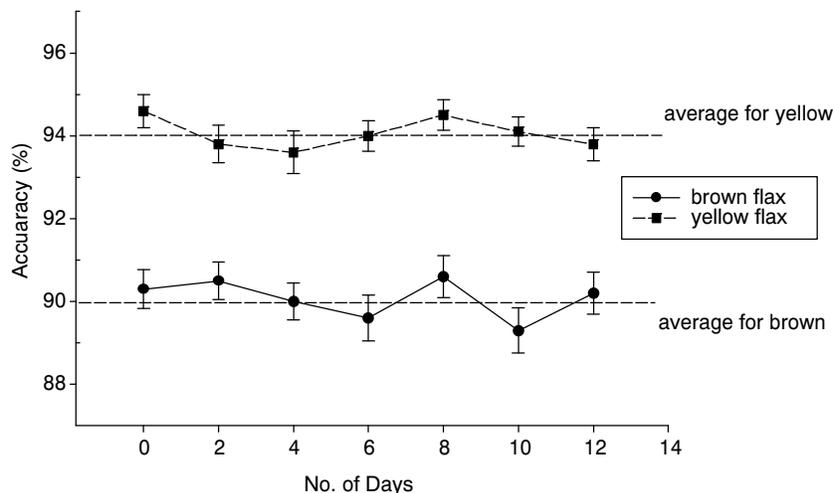


Figure 8. Average sorting accuracies for each day of testing of the sorting system running brown and yellow flax seed.

cost effective and useful tool to seed breeders and seed suppliers. Cleaner seed will also help farmers to produce a more pure crop, which could help in international trade.

While the training process only takes approximately 10 min, it appears that it will not need to be performed very often for a given application. The lighting from the LED is very stable and the observed accuracy over 12-day periods showed no sign of declining over time. While dust covering the camera lens and LED's was not observed to be an issue during the testing, daily cleaning of the lenses may be needed if the machine is used constantly throughout the day. This is required on commercial sorters as well. The light intensity emitted by the LED's does gradually decay over several months' time, so the sorter would have to be eventually re-trained to account for lighting changes. It is more likely that the sorter would need to be re-trained more often to accommodate seed being supplied from different regions and growing conditions.

CONCLUSION

Simple image processing and pattern recognition can be executed in hardware on FPGA chips directly linked to image sensors. This combination makes an economical system for the inspection of agricultural products, which until now has not been reported. The throughput of this three-channel system, ~25 kg/h wheat (about 225 kernels/s) is unprecedented for an imaging based system. The high throughput is made possible by utilizing parallel processing of three separate channels of wheat on one image sensor/FPGA device. Sorting accuracy is comparable to what has been accomplished so far using traditional color cameras, with image processing performed on personal computers. Training of the system with small amounts of two classes of seeds can be accomplished in about ten minutes. It appears that the sorter can operate with consistent classification results for several days without the need to re-train it. This system was tested on a range of seed sizes from flax seed to

large barley seeds. It may be possible to inspect larger products such as corn and tree nuts with modifications to the feeding system. Parts for the system are lower in cost and physically more robust than systems using personal computers, so they might be more suitable for processing plant environments.

ACKNOWLEDGEMENTS

Author appreciates assistance from Dr. Daniel Brabec during fabrication of sorter prototype.

REFERENCES

- Delwiche, S. R., T. C. Pearson, and D. L. Brabec. 2005. High-speed optical sorting of soft wheat for reduction of deoxynivalenol. *Plant Disease* 89(11): 1214-1219.
- Ghazanfari, A., J. Irudaraj, A. Kusalik, and A. Romaniuk. 1997. Machine vision grading of pistachio nuts using Fourier descriptors. *J. Agric. Eng. Res.* 68(3): 247-252.
- Maxfield, C. M. 2004. *The Design Warrior's Guide to FPGA's*. Burlington, Mass.: Newnes Press.
- Majumdar, S., and D. S. Jayas. 2000a. Classification of cereal grains using machine vision: II. Color models. *Trans. ASAE* 43(6): 1677-1680.
- Majumdar, S., and D. S. Jayas. 2000b. Classification of cereal grains using machine vision: IV. Combined morphology, color, and texture models. *Trans. ASAE* 43(6): 1689-1694.
- Pasikatan, M. C., and F. E. Dowell. 2003. Evaluation of a high-speed color sorter for segregation of red and white wheat. *Applied Eng. in Agric.* 19(1): 71-76.
- Pearson, T. C., D. L. Brabec, and S. Haley. 2008. Color image based sorter for separating red and white wheat. *Sensing and Instrumentation for Food Quality and Safety* 2(4): 280-288.
- Pearson, T. C. 2009. Hardware based image processing for high-speed inspection of grains. *Computers and Electronics in Agric.* 69(1): 12-18.

