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ORIGINAL PAPER

Color image based sorter for separating red and white wheat

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Abstract A simple imaging system was developed to inspect and sort wheat samples and other grains at moderate feed-rates (30 kernels/s or 3.5 kg wheat/h). A single camera captured color images of three sides of each kernel by using mirrors, and the images were processed using a personal computer (PC). Real time image acquisition and processing was enabled on an ordinary PC under Windows XP operating system using the IEEE 1394 data transfer protocol, DirectX application software, and dual-core computer processor. Image acquisition and transfer to the PC required approximately 17 ms per kernel, and an additional 1.5 ms was required for image processing. After classification, the computer could output a signal from the parallel port to activate an air valve to divert (sort) kernels into a secondary container. Hard red and hard white wheat kernels were used in this study to test and demonstrate sorter capability. Simple image statistics and histograms were used as features. Discriminant analysis was performed with one, two, or three features to demonstrate classification improvements with increased numbers of features. The sorter was able to separate hard red kernels from hard white kernels with 95 to 99% accuracy, depending on the wheat varieties, feed-rate, and number of classification features. The system is an economical and useful instrument for sorting wheat and other grains with high accuracy.

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Introduction

The use of imaging for high-speed sorting of agricultural products has been limited, in part, by the high cost of imaging and processing hardware for real-time applications. Traditionally, images are captured using a "frame grabber" card hosted inside a PC. The frame grabber may have some real-time digital signal processing capabilities, but all outputs and decision making must be processed by the PC. Thus, for high-speed image-based sorting applications, the PC operating system must have the capacity to operate in real time, using critical timings as short as two milliseconds. This adds to the cost and complexity of the overall system. A high-speed image-based sorting device for almonds using a PC running under the DOS operating system was developed [10] to save the cost of a real time operating system and computer. Using a frame grabber and two linescan cameras, the system was able to inspect almonds at a rate of 40 nuts/s. However, the cost of the parts alone for this system was over $10,000 and the images were mono-chromatic.

Most commercial high-speed sorting machines used for agricultural products either have no spatial resolution or do not fully utilize the spatial resolution produced by their sensors. These devices perform limited signal processing in hardware for robustness and high speed, rather than on a micro-processor or PC. For those sorters with some spatial resolution ($\sim$0.2 mm/pixel), the only image processing performed is thresholding and pixel counting. Consequently, for many products, certain defects are difficult to detect and remove using currently available commercial sorters. Shriveled and *Fusarium* head blight (scab) damaged wheat kernels are a case in point. The efficacy of using a limited spatial resolution ($\sim$0.5 mm) commercial dual-band (one near infrared (NIR), one visible) sorter for removal of scab-damaged kernels has been studied [4]. Only 50% of the scab-damaged kernels were removed, while about 5% of the undamaged kernels were also rejected. Preliminary studies have shown that the use of simple histograms of moderate resolution images enables scab-damaged kernels to be distinguished from sound kernels with over 90% accuracy [9].

Commercial color sorters can have throughputs as high as 1200 kg/h for wheat. This is accomplished by running as many as 80 channels in parallel within one machine. Thus, each channel has a throughput rate of approximately 15 kg/h, or about 126 kernels/s for wheat. While sorter throughput of this magnitude is needed to meet processing plant requirements, this is often more than is needed for smaller scale operations such as seed cleaning and selection for plant breeders. With wheat breeding, color sorting would be useful in early generations, when segregating breeding populations, or in later breeding generations, where breeding lines contain mixed color classes due to natural heterogeneity or admixture. In the case of early generation populations, wheat breeders would typically have only small quantities of grain available for sorting, usually less than 5 kg. In this situation, lower throughput with associated lower machine cost and higher accuracy is more desirable.

Charge coupled devices (CCD) have traditionally been the most common image sensors used. While these devices produce high quality images at very high resolution, they require significant support electronics [16]. However, this need for elaborate support electronics for image sensors has recently been alleviated by the now widespread production of complementary metal–oxide–semiconductor (CMOS) image sensors [12]. Production of CMOS devices is less expensive than that required for charge coupled devices (CCD), and the required support electronics are integrated onto the sensor chip. Additionally, support electronics, such as external triggering inputs and analog-to-digital converters, have been added to low-cost cameras that transfer images from camera to PC through IEEE 1394 or Universal Serial Bus (USB) ports. Of these two transfer protocols, IEEE 1394 is preferred for high-speed, real-time, applications as it supports true direct memory transfers without the need for the computer processors or operating system to manage the data transfer [1]. In other words, the camera is able to load the images into PC memory on its own, without additional processing by the PC.

Finally, direct memory transfers and image manipulation are enabled in real time on Microsoft Windows operating systems by an application programming interface called DirectX [6]. This interface was initially developed to provide enhanced video and audio handling capability for computer games with advanced high-resolution graphics. However, capabilities for cameras connected by IEEE 1394 cables are also available, and can be exploited in real-time imaging applications on Microsoft Windows operating systems, including Windows XP and Vista.

There have been many developments relevant to the inspection of agricultural products using imaging, such as inspection of apples [2], rice [5], and wheat [14]. However, few of these developments are able to be implemented as high-speed sorting applications at an economically feasible cost. Few developments where sorter throughput and cost are considered have been reported in the literature. A vision-based sorting machine system that identified staining patterns on pistachio nuts, where these indicated aflatoxin contamination has been developed [8]. This system performed some image processing and maintained a sorting rate of 40 nuts per second per channel. In this system, the spatial resolution was very low since the maximum data transfer rate between camera and processor used was low (250 kHz over an 8-bit bus). This allowed the processing to be performed on a low cost digital signal processor, without the need for a PC. However, the low spatial resolution of the device reduced its applicability to other sorting problems. More recently, an image-based sorter based on transmitted light in order to detect almonds with shell fragments embedded into the kernel was developed [10]. Another low-cost machine vision system was developed to inspect meat for foreign objects using color [11]; however, this system does not perform sorting. A color imaging system was developed for inspection and sorting of grains at rates of over 30 kernels/s [13]. However, this system only images one side of the kernel. Reflectance color and monochromatic transmittance imaging algorithms were developed to aid inspection of small grains using a commercial imaging device [15]. This device was able to inspect single kernels at rates approaching 20 kernels/s, and could perform moderate image processing at this inspection rate. However, this machine has a high cost and does not perform sorting. A dual-wavelength machine vision system for inspection of chicken carcasses was developed [3]. This device utilizes a high degree of image processing through neural networks and can inspect chickens at rates over two per second. This device uses traditional CCD cameras, frame grabber boards, and a PC for processing images. Finally, robust, low-cost color machine vision systems for industrial inspection (e.g. Banner Engineering Corporation) are now becoming available to distinguish objects with large color differences. These devices require a large color difference to be distinguished and do not have the throughput rate (over 20 objects/s) to be practical for inspection of most agricultural products, such as grains.

The objectives of this research were to develop a laboratory-scale sorting device which improved the uniformity of breeder's wheat samples. Secondly, this research studied the classification performance of this sorting device when using a single feature (as used by commercial color sorters) versus multiple image features. While the feed-rate of a single channel imaging system cannot match those of commercial color sorters, the system could find uses where accuracy is more of a factor than throughput.

Materials and methods

Image and sorting system hardware

Figure 1 depicts a machine vision system linked to a personal computer. The camera (DFK21BF04, The Imaging Souce, Sommerstrabe, Germany) is a color camera utilizing a Red-Green-Blue (RGB) Bayer pattern filter over a total of 640 × 480 pixels. The camera transfers images to the computer via an IEEE 1394 cable in direct memory access (DMA) mode using the DirectX application programming interface (DirectX version 9.0, Microsoft Corp. Redmond, WA). Images are transferred in raw format without color interpolation, in order to reduce the amount of data transmitted from the camera by one-third. The camera uses a 25 mm C-mount lens (M2514-MP, Computar, Japan).

A photo-electric switch (D21DAB6FP05, Banner Engineering, Minneapolis, MN) was used to externally trigger the camera, allowing image acquisition to be performed in hardware, external from the computer. As such, the kernel position is very consistent at the moment of image acquisition. The position of the leading edge of the kernel varies only 1 mm from image to image.

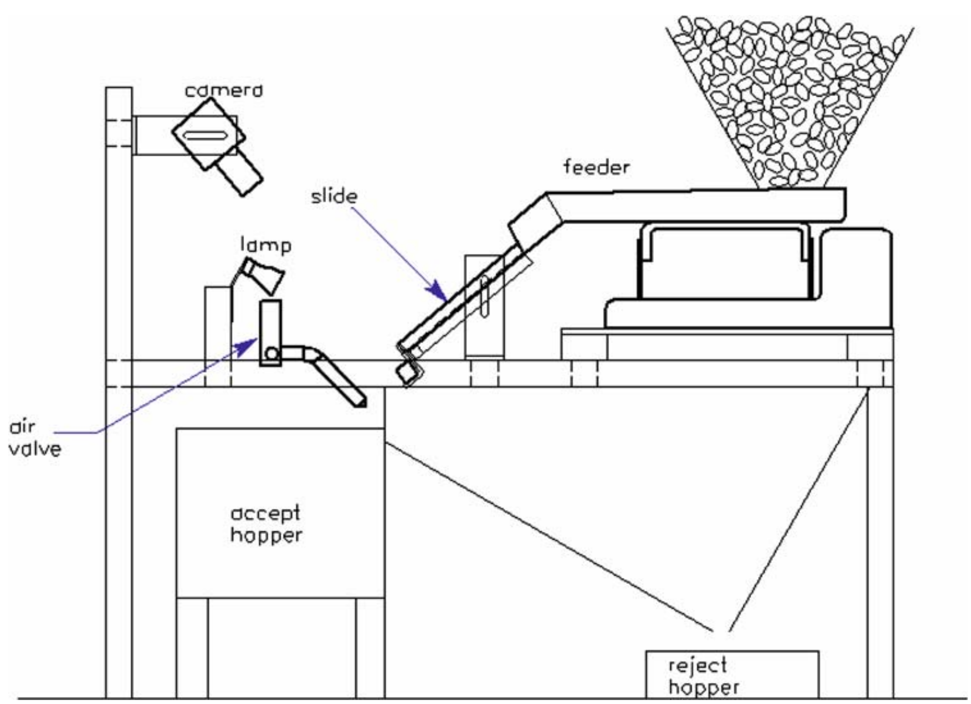
Images from the backside of each kernel (opposite of the camera) are reflected back to the camera with two 45° mirrors (RA EN AL 20 × 28 mm, Edmund Optics, Barrington, NJ). This allows capture of the entire perimeter of each kernel with one image and one camera, simplifying the system design and lowering the overall cost.

The kernels were illuminated with two small 35 W reflector lamps (12V35 W/N/FG—MR8, Ushio, Japan). The shutter speed of the camera was set at a constant 1/6875 s and a gain of 500 (the range for this camera was 1–1,000). White balance was set using a flat piece of white Teflon placed over the mirrors. Before performing any sorting, the camera captured a blank image with no kernel as well as a gray image using a standard 18% gray reflector card (421869, X-rite Inc. Grand Rapids, MI).

The feeding system was two-staged, comprising a seed metering device and a vibratory feeder. An auger style metering device (3010FC/B, Seedburo Equipment Co, Chicago, IL) metered wheat onto the feeder's v-trough. The vibratory feeder (F-TO-C, FMS-Syntron, Homer City, PA) advanced kernels onto a slide which also had a v-shape. The slide was 15 cm long and fabricated out of aluminum bar stock. Kernels accelerated and separated on the slide so that only one kernel would appear in each image.

The feed-rates were varied by changing the motor on the metering device. The 15 RPM (Bodine KYC-24T4), 22

Fig. 1 Schematic of automated imaging device



RPM (Bodine KCI-24T4), and 30 RPM (Bodine KYC-24T3) motors delivered 30, 60, and 90 g/min which corresponded to 15, 30, and 45 kernels/s, respectively.

After image capture, analysis, and classification, if a kernel was classified as white, an air valve (35A–AAA–DDBA–1BA, Mac Valves, Inc., Wixom, Mich.) was activated to divert these kernels from the red kernels into a separate hopper. This valve was chosen for its fast response time and longevity. While the manufacturer does not specify a life expectancy for this valve, these valves have been used over several years on other sorting machines in processing plants without failing. A wide air nozzle (31875K41, McMaster-Carr Co. Elmhurst, IL) was used to ensure proper rejection. The air valve was activated by outputting a signal from the computer's parallel port which was used to trigger a timer circuit to control the air blast duration. This external circuit allowed the computer to be available to process another kernel while the air valve was opened. It was found, by trial and error, that an air blast duration of 5 ms was sufficient to remove 99% of the kernels when fed at a rate of 15 kernels/s.

Image processing and analysis

Each image had 480 rows and 640 columns of pixels. Rather than color interpolating the images, the red, green, and blue pixels from the Bayer filter pattern (alternate lines had blue-green and red-green pixels) were separated to form three images of 240 × 320 pixels in size. A kernel's length would span 100–150 pixels. The leading edge of the kernel would vary by approximately 30 pixels from the top of the image. Since the kernel was consistently in the center of the image frame, the first 20 rows and last 20 rows of each 240 × 320 image were not processed to reduce image processing time.

The first image processing step was to subtract the blank image, acquired prior to sorting, from the new image containing the kernel. Only the red image pixels were subtracted in this step as the red pixels were less prone to noise since the sensor sensitivity is greater at light corresponding to red wavelengths. When the intensity between the red pixels of the blank image and the red pixels from the new image was greater than 10, these pixels were considered to be part of the kernel. If the difference was less than or equal to 10, the red pixels and adjacent blue and green pixels were set to zero and considered background. This enabled nearly flawless segmentation of the kernel from the background. The threshold settings were determined by trial and error before experiments began but were kept the same for every subsequent experiment.

The pixel intensities of the red, green, and blue images were then scaled using the image of the 18% gray card. The average intensity values for the gray card were approximately 128 for the red, green and blue color channels. Due to the inconsistent light coverage from the lamps and the wheat kernel's geometry, the edges of each image were darker than the center. To equalize the lighting distribution and help make a calibration repeatable over time, the intensity of every kernel pixel from each corresponding red, green, and blue image was divided by the intensity of the corresponding gray card image pixel, then multiplied by 128.

Three intensity histograms were extracted as features for classification. Each histogram represented the scaled red, green, or blue pixel intensities from the wheat kernel image. The bin type histograms were converted to cumulative histograms and then to percent kernel pixels by scaling with the total number of pixels within the kernel. This normalized the histograms for varying kernel sizes. Each histogram contained 64 bin levels representing intensity levels from low to high. The three histograms produced '3 × 64' or 192 potential image features. In addition, the mean and standard deviation of the red, green, and blue intensities were computed, resulting in six more features. Thus, from the three histograms, means, and standard deviation pairs, a total of 198 features were computed for each kernel image.

Wheat sorter software and training

Prior to sorting wheat samples, the image sorter software was trained using data from 200 typical red kernels and 200 typical white kernels. Linear discriminant analysis was used as the classification method using a small subset from the pool of image features. The data was randomly divided into equal training and validation sets. The training set was used to compute the group means and covariances of the feature subsets. The validation set was used to test the classifications. An exhaustive search was used to test all possible one-, two-, and three-feature combinations. The best discriminating single-, two-, and three-feature combinations were selected to be used for sorting. The whole training process took less than 5 min to perform per sample pair.

Wheat sorter tests

The wheat sorter has two distinct functions. The camera collects images and discriminates with some level of classification efficiency. Secondly, the system removes moving kernels with a blast of air with some level of ejection efficiency. The overall efficiency of the sorting system is a combination of these two efficiencies. For instance, if the images are discriminated with 95% accuracy and the ejectors can remove 95% of the kernels passing by, then the overall efficiency of the system is 95% × 95%, or 90%.

The image classification efficiency was affected by the number of features used in the classification (1, 2, or 3) and the contrast between the red and white samples. The ejection efficiency was affected by the sample feed-rate, mixture level of red and white kernels, and computer process timing.

The sorter was tested with two reference red/white wheat pairs. One pair had good contrast between the red and white kernels and was easy to distinguish by the human eye. The second pair had less contrast and thus was more difficult to distinguish. This was due to some of the red wheat kernels being lightened from weathering, in addition to the white kernels having a more beige, rather than white, appearance. The white kernels from the difficult sample were marked with an invisible ink (U.V. Security Marker Ink 57-52-E1, Blacklight World, Cub Run, KY) that fluoresces under UV light but is otherwise invisible. After sorter testing with these kernels, the samples were inspected under UV light to determine sorter accuracy. Images of kernels from the two samples are shown in Fig. 2.

The sorter software was trained and tested separately with each reference wheat pair. Then, a sample was mixed from the reference wheat which contained 95 g of hard red wheat and 5 g of hard white wheat. The sorter was set to reject the white kernels with the air valve since they were the smaller portion. Sorting tests were performed with the best three feature combinations for each reference wheat pair.

The sorter was tested at rates of 1, 15, 30, and 45 kernels/s to determine if higher throughput rates caused more errors due to kernels touching each other as they are imaged and rejected. Each sample was run through the machine 10 times at each of the four sorter throughput rates. The feed rate was adjusted by changing the motors on the auger metering feeder, as discussed earlier. The average and standard deviation of the sorting accuracies were recorded. Additionally, data were collected to quantify the time intervals between kernels for the different feed rates of 15, 30, and 45 kernels/s.

System sorting and lamp stability were tested over five consecutive days. Before testing the sorter each day, a

Fig. 2 Images of red (left) and white (right) kernels from the easy sample (top row) and difficult sample (bottom row). Note that the contrast between the red and white kernels is greater for the easy sample than the difficult sample. Also note that the many red kernels from the difficult sample have a yellow hue, these are called "yellow berries"

new image of the 18% gray card and a blank image were acquired for kernel segmentation and pixel intensity scaling. The sorter was tested at the 30 kernels/s rate only. Two mixed wheat samples were run through the machine ten times each day and the average and standard deviation of the sorting accuracies were recorded each day. It is important to note that the sorter was trained only once before all testing began. The lamps on the sorter remained on for the entire week so there would not be any error due to lamp warm up. One hundred kernels from the two red and white samples were used for this test.

To test the image collection and processing times, software was written to output a pulse from the parallel port upon receipt of a new image and after all image processing was completed. The times between pulses was then measured on a digital oscilloscope (196C, Fluke Inc., Everett, WA). Three different computers were tested, all using the Windows XP operating system. One computer contained a single-core Advanced Micro Devices (AMD) Athlon 3000+ processor with 2 GB of 400 MHz DDR SDRAM (XC Cube EX761, AOpen Inc., Milpitas, CA). The second computer contained a dual-core AMD X2 Athlon 6000+ processor with 2 GB of 800 MHz DDR2 SDRAM (Pundit P1-AH2, ASUS Computer International, Freemont, CA). The third computer used an Intel Core Duo 6600 processor with 2 GB of 667 MHz DDR2 SDRAM (Optiplex 745, Dell Computer, Round Rock, TX). The image transfer and processing times from 30 kernels were recorded for each computer.

Results

Image transfer and processing timings

As shown in Table 1, the dual-core processors have faster image processing times and, more importantly, much more consistent times than the single-core processor. The fastest average time to recognize a new image and process it was 18.3 ms with a standard deviation of 0.6 ms (17.2 ms to recognize the image and 1.1 ms to process it). This was obtained with the computer using the AMD Athlon 64 X2 6000+ dual-core processor. The timings from the computer using the Intel Core Duo 6600 processor were slightly slower than, but just as consistent as the AMD dual-core processor. The PC with the Intel processor may have been slightly slower due to the slower memory speed in this computer. After receipt of a trigger signal, the camera requires 16.7 ms to acquire and transfer an image into the computer. The average time of 17.2 ms for a PC to recognize that a new image has been transferred indicates that the PC required 0.5 ms to recognize it after the image was completely loaded. The timings from the computer having the single-core AMD Athlon 3000+ processor were, on average, 3.7 ms slower. More importantly, however, these timings were much more variable, with a standard deviation of 3.5 ms. Assuming a normal distribution, the PC with the AMD Athlon 64 X2 6000+ dual-core processor would be able to process over 95% of the kernels within a 2.4 ms window, while the single-core AMD Athlon 3000+ processor requires a window of 14.0 ms. Given that the kernels are traveling at approximately 2 m/s, this means that the kernel position uncertainty from the single-core processor is 28 mm, compared to only 4.8 mm for the dual-core processor. Having a lower time uncertainty in this sorting system allows the air valve blast duration to be shorter and reduces the likelihood of rejecting two kernels with one air blast. For this reason, in all further tests, the computer with the dual-core AMD Athlon 64 X2 6000+ processor was used. Use of this computer allowed the air valve blast duration to be set at 5 ms, which enabled the sorting throughput to be relatively high. Windows XP and Vista operating systems have traditionally not been considered to be capable of real time operatations. The combination of image triggering in hardware, DMA image transfer to a computer via IEEE 1394 protocol, DirectX API and dual core processors appear to give adequate real time capability for this application. Since this software and hardware has lower cost and is much easier to program than traditional real time hardware and software, this finding should stimulate more real time applications with the configuration used in this study.

Table 1 Average time to recognize a new image after kernel breaks the trigger, and average image processing times in milliseconds for the three computers tested

	ASUS—AMD Athalon 64 X2 6000+		Aopen—AMD Athalon (single core) 3000+		Dell Optiplex 745—Intel Core Duo 6600 2.4Ghz	
	Time to recognize new image	Image processing time	Time to recognize new image	Image processing time	Time to recognize new image	Image processing time
Average	17.2	1.1	20.3	1.7	17.3	1.6
Std dev	0.5	0.1	3.4	0.1	0.5	0.1

Feature selection and classification

Validation set classification accuracies for both the "easy" and "difficult" samples are shown in Table 2. For the easy sample, the best feature subset for distinguishing hard red wheat from hard white wheat kernels was comprised of three features: the mean of the green pixels; the percentage of blue pixels with an intensity less than 112; and the percentage of red pixels having an intensity less than 176. White wheat kernels tended to have higher values for the mean green pixels, indicating an overall brighter appearance. Although the white kernels were brighter overall, they had a higher percentage of red pixels with a low-to-moderate intensity (176) than the red kernels did. Conversely, the red kernels had higher percentages of blue pixels with low-to-moderate intensities (less than 112). Since red colors absorb blue light, it is not surprising that a higher percentage of red kernels had lower blue pixel intensities than the white kernels. Validation set accuracy indicated that that accuracy for red wheat should be 98%, while the accuracy for white wheat should be 99%, for an average accuracy of 98.5%. When only one or two features are selected, the average accuracy reduces to 94% for two features and 88% for one feature. The accuracy for one feature is an indication of what could be accomplished with a mono-chromatic sorting device such as those available from Satake USA, Inc, Sortex, etc. The effectiveness of a commercial monochromatic color sorting machine for separating hard white wheat from hard red wheat has been studied [7]. The result of this study was that, depending on the variety and amount of weathering the red kernels incurred, the sorting machine needed to reject 15 to 20% of all material in order to remove 80 to 90% of the red wheat from the white. The 88% classification accuracy, when using only one image histogram feature for kernels that have high contrast between them, is consistent with the results from [7].

While the "difficult" sample had similar classification accuracies as the "easy" sample, the features selected were different. The best average classification accuracy (97%) for this set also required three features. These features were: the percentage of red pixels with an intensity less than 64, the percentage of blue pixels having an intensity less than 72, and the standard deviation of the red pixel intensities. The red kernels had higher counts of low intensity blue pixels, higher counts of red pixels with low intensities, and higher standard deviations of red pixel intensities. While the red kernels in this sample also had higher percentages of high-intensity red pixels than white kernels, similar to the easy sample, the classification in this case is based more on the darker portions of the red kernels. Many of the red kernels in this sample contained some darker areas as well as very light areas from weathering. This causes the standard deviation of the pixel intensities of the red kernels to be high, whereas the white kernels tend to have more consistent intensity levels across their entire surface.

Table 2 Classification results from linear discriminant analysis on the training sets of the "easy" and "difficult" samples

Number of features selected	Accuracy for the "easy" sample		Accuracy for the "difficult" sample	
	Red	White	Red	White
1	86	91	88	78
2	92	96	92	85
3	98	99	97	97

Discrete histogram values and average pixel values could be approximated by single sensors coupled with the appropriate color filter, such as those used in commercial color sorters; however, the variance of pixel intensities requires an image and simple image processing to compute. Even though this is a simple feature to extract from an image, it improves classification accuracy of kernels in the "difficult" sample. When the pixel standard deviations are removed from the pool of features, the best three-feature classification accuracy obtained was 93% for hard red wheat and 90% for hard white wheat for an average accuracy of 91.5%. Conversely, the average accuracy when selection of the standard deviation of the red pixels was allowed was 97% (Table 2).

Sorter testing

The accuracy of a sorting system is dependent on robust image processing and classification as well as efficient mechanical feeding and sorting. When the feed rate increases, errors can occur due to kernels being too close to one another. The camera requires approximately 17 ms to capture and transfer an image to a PC. If kernels are separated by less than this time period, these kernels are not imaged correctly, or are missed entirely. Additionally, kernels that are too close to another kernel can be diverted together with a single air blast. The air valve needs to be open for a minimum of 5 ms to account for variations of the potential kernel position with respect to the air blast.

Testing of the sorter at feed-rates of 1, 15, 30, and 45 kernels/s shows how accuracy decreased as throughput increased. Table 2 displays sorting results versus feed-rate. The accuracies for throughputs of 1 and 15 kernels/s are almost identical, and close to the accuracies achieved when training. This indicates that kernels fed at a rate of 15 kernels/s are well-separated so that only one kernel is in the field of view at a time. The time gaps at 15 kernels/s averaged 67 ms, and the minimum time gap was 30 ms (from a 100 kernel sample). When the throughput was increased to 30 kernels/s, the accuracy dropped by an average of 1.2%. This slight drop in accuracy may be tolerable, because the feed-rate increased and the sample processing time was cut in half. The accuracies at a throughput of 45 kernels/s dropped an average of 12.0%.

The increased feed-rates affected accuracy for white wheat more than red wheat since the higher feed rate caused some kernels to be ignored. The kernel separation times at the 45 kernels/s feed-rate ranged from 12 ms to 44 ms. The average time gap was 22 ms. Most of the kernels had separation times of 17 ms to 28 ms. However, 15% were separated by less than 17 ms, which is the minimum time necessary for proper imaging. In contrast, when kernels were fed at a rate of 30 kernels/s, only 2% were separated by less than 17 ms.

The image processing for this application took less than 1.5 ms while the image transfer time required nearly 17 ms. If the computer had access to the image data before the entire image was transferred, this could possibly allow enough time for more elaborate image processing to be performed without sacrificing any throughput. This will be the basis of future study and development.

Two wheat samples were repeatedly sorted over a five day period. As can be seen from Fig. 3, there is no significant trend over that period. This indicates that the sorter can perform for at least a five day period with one calibration. However, a new image of the 18% gray card and new blank image are acquired each day to scale the image. Even though the discriminant function can be re-trained within 5 min, it is important for the sorter performance to be repeatable over a reasonably long time span (Table 3).

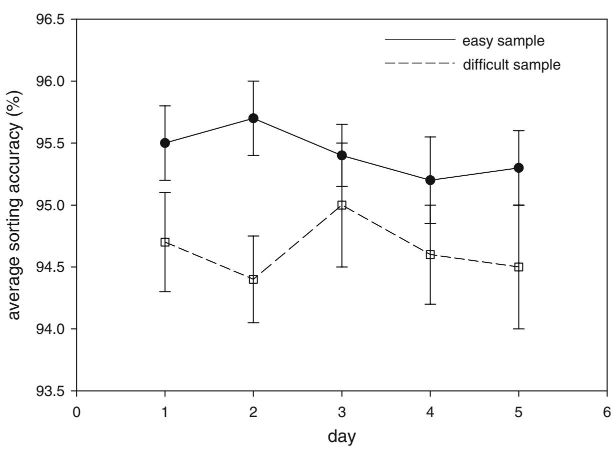


Fig. 3 Average sorting accuracies for the easy and difficult sample over a five day period and feed rate of 30 kernels/s. Note that there is no significant trend over the five day period

Conclusion

The image sorting system has low cost and a moderately high throughput of 30 kernels/s. Real-time sorting is enabled by the use of IEEE 1394 direct memory access image transfer, DirectX, and dual-core processors available in low cost PCs. The sorter appears to be nearly as accurate at separating wheat samples with low contrast differences as it is with samples having high contrast. With image processing, three features were extracted and showed to more accurately discriminate red and white wheat samples than a single feature, as is performed with commercial color sorters. In particular, standard deviation features provided unique and helpful information with kernels of more variable color.

Sorting at throughputs of 15 kernels/s and below showed that the actual sorting accuracy is very near the validation set accuracy. Sorting at throughputs of 30 kernels/s showed reduced sorting accuracies by an average of only 1.2%. Feed-rates of 45 kernels/s reduced accuracies by an average of 12%.

When operating the sorter at a throughput of 30 kernels/s, the accuracy for the two samples studied was, on average, 95.5% and 94.7% for the “easy” and “difficult” samples, respectively. These sorting accuracies are over 10% greater than what can be expected from commercial color sorters. Given the low cost, accuracy, and moderate throughputs of the image sorting system, this device should prove to be practical where accuracy is more important than throughput, such as with wheat breeding applications where it may be desirable to sort red and white wheat from mixed samples. Other grain applications will be studied in the future, including the sorting of scab damaged wheat and fungal damaged popcorn.

Table 3 Average and standard deviations from sorting tests at various throughput rates for the two samples

Throughput rate (kernels/s)	Easy sample		Difficult sample	
	Accuracy for white wheat	Accuracy for red wheat	Accuracy for white wheat	Accuracy for red wheat
1	98.1 (0.1)	95.9 (0.2)	96.0 (0.2)	95.1 (0.2)
15	98.0 (0.1)	95.8 (0.2)	95.9 (0.3)	94.9 (0.3)
30	96.1 (0.2)	94.9 (0.5)	95.5 (0.3)	93.9 (0.5)
45	90.1 (1.6)	78.2 (1.9)	89.9 (1.8)	76.0 (2.2)

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