AUTOMATED DETECTION OF INTERNAL INSECT INFESTATIONS IN WHOLE WHEAT KERNELS USING A PERTEN SKCS 4100

T. C. Pearson, D. L. Brabec, C. R. Schwartz

ABSTRACT. *The wheat industry is in need of an automated, economical, and rapid means of detecting whole wheat kernels with internal insect infestation. The feasibility of the Perten Single Kernel Characterization System (SKCS) to detect internal insect infestations was studied. The SKCS monitors compression force and electrical conductance as individual kernels are crushed. Samples of hard red winter (HRW) wheat and soft red winter (SRW) wheat infested with rice weevil [*Sitophilus oryzae *(L.)] and lesser grain borer [*Rhyzopertha dominica *(F.)] were run through the SKCS and the conductance/force signals saved for post-run processing. Algorithms were developed to detect kernels with live internal insects, kernels with dead internal insects, and kernels from which insects have emerged. The conductance signal was used to detect live infestations and the force signal for dead and emerged infestations. Live insect detection rates were 24.5% for small-sized larvae, 62.2% for medium-sized larvae, 87.5% for large-sized larvae, and 88.4% for pupae. The predicted, and observed, false positive (sound kernels classified as infested) rate was 0.01%. Dead insect detection rates were 60.7% for large-sized larvae, 65.1% for pupae, and 72.6% for kernels where the insect emerged. The false positive rate of the dead insect detection algorithm ranged from 0.2% for SRW to 0.5% for HRW. In all cases, insect detection rates were higher for rice weevil than lesser grain borer. The classification algorithms were robust for a wide range of moisture contents.*

Keywords. *Weevil, Conductance, Crush force.*

Internal insect infestation of wheat kernels degrades quality and value of wheat and is one of the most difficult defects to detect. Insect infestation causes grain loss by consumption, contaminates the grain with excrement and fragments, causes nutritional losses, and degrades end-use quality of flour (Sanchez-Marinez et al., 1997; Pederson, 1992). While stored grain is vulnerable to both external and internal damage by insects, internal infestations are generally considered the most damaging (Pederson, 1992). Five species of insects develop through larval stages and into adults while inside of wheat kernels. The development time ranges from four to seven weeks during which visible signs of seed damage are not apparent. The insect leaves an exit hole in the seed once the insect reaches the adult stage and emerges. These are the rice weevil [*Sitophilus oryzae* (L.)], maize weevil [*Sitophilus zeamais* (Motsch)], granary weevil [*Sitophilus granarius* (L.)], lesser grain borer [*Rhyzopertha dominica* (F.)], and angoumois grain moth [*Sitotroga cerealella* (Olivier)]. Angoumois grain moth infestations are usually limited to the top few inches of the bin for stored grain, while the other insects can infest grain in pockets anywhere in the bin. Weevils and lesser grain borer insects have been identified as the most common internal infesters of wheat (Storey et al., 1982).

United States wheat standards consider kernels as insect damaged when exit tunnels or holes are observed on the kernel surface (Federal Grain Inspection Service, 1997). However, insects have already emerged from these kernels. A wheat load is reduced to U.S. Sample Grade if 32 or more insect-damaged kernels are found in a 100 gram wheat sample (Federal Grain Inspection Service, 1997). Inspecting for insect-damaged kernels is labor intensive and may miss most of the infested kernels where an immature insect has not emerged from the kernel. Storey et al. (1982) reported that as many as 12% of all wheat samples from export loads have hidden internal insects but go undetected during the normal grain inspection process. Grain inspectors at milling facilities need to know the quantity of kernels with hidden insect damage so that loads with excessive infestations can be cleaned or diverted for other uses.

Several methods have been used, or are currently under development, to detect insect damage inside whole wheat kernels. Pederson (1992) reviewed many of the techniques for detecting internal insects. These methods include staining the egg plug to detect weevil infestation, flotation methods, x-ray imaging, acoustic detection of larval movement and chewing, carbon dioxide measurement, and staining of amino acids specific to insect body fluids. However, most of these methods have only achieved limited implementation either because they are slow, labor intensive, expensive, or can only detect specific insect species. In more recent work, Haff (2001) developed an image analysis program to automatically scan x-ray images for insect infestation. Other researchers have investigated the use of near-infrared (NIR) spectroscopy to detect hidden insects in wheat kernels (Dowell et al., 1998; Ridgway and Chambers, 1996;

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The authors are **Tom C. Pearson, ASAE Member Engineer,** Agricultural Engineer, **Daniel L. Brabec, ASAE Member Engineer,** Engineering Technician, **Carrie R. Schwartz, ASAE Student Member,** Engineering Technician, USDA-ARS-GMPRC, Manhattan, Kansas. **Corresponding author:** Tom Pearson, USDA-ARS-GMPRC, 1515 College Avenue, Manhattan, KS 66502; phone: 785-776-2729; fax: 785-537-5550; e-mail: tpearson@gmprc.ksu.edu.

Ghaedian and Wehling, 1997). Both x-ray and NIR spectroscopy can detect internal insects with high accuracy, and cost of the required equipment has fallen in the past few years. However, x-ray and NIR instrumentation suffer from high false positive error rates (good kernels classified as infested), are still cost prohibitive for many commercial applications, and current NIR instrumentation requires complex procedures and calibrations (Dowell et al., 1998). Thus, no economically viable and simple equipment utilizing these technologies has yet become available for grain inspectors to use to detect internal insects.

The single-kernel characterization system (SKCS) (SKCS 4100, Perten Instruments, Springfield, Ill.) measures kernel weight, moisture content (MC), diameter, and hardness at a rate of two kernels per second, and reports the average and standard deviation of these parameters from a 300-kernel sample. These systems are used worldwide in many inspection facilities to determine the physical properties of wheat. To measure MC and hardness, electrical conductance and compression force are monitored and stored by the SKCS, while a kernel is crushed between a corrugated rotor and crescent (Martin et al., 1993). Since a live insect has a much higher MC than properly stored sound wheat kernels, it may be that the presence of live internal insects can be detected through processing the conductance signal during crushing. Additionally, the force signal may be useful for detecting internal tunnels created by insects that have died and dried out inside the kernel or where the insect has matured and emerged from the kernel. The objective of this study was to determine the feasibility of using the standard hardware of the SKCS to detect kernels with live internal insects, kernels with dead internal insects, and kernels from which insects have emerged.

Experimental Procedures

Insect Rearing and Maturity Estimation

Two species of insects, the rice weevil and the lesser grain borer, were reared in kernels from two different wheat classes, hard red winter (HRW) and soft red winter (SRW), for a total of four insect-wheat class combinations. The HRW wheat was of the Pioneer 2180 variety, grown in central Kansas, and harvested in 2000; while the SRW wheat was of the Caldwell variety, grown in Ohio, and harvested in 1994. Both stocks of wheat were stored at 10°C after harvest. Insect rearing was performed in quart-sized jars with screen lids, with approximately 350 g of wheat and 300 adult insects. The jars were incubated at 26°C and 60% RH. Starting at the second week after incubation began, samples of kernels were removed on a weekly basis until the end of the sixth week. These samples were radiographed using a cabinet x-ray system (#43855A, Faxitron Corp., Wheeling, Ill.), with 13- × 18-cm film (Kodak Industry M film, France), at an exposure of 18 kV and 3 mA for 2 min. To estimate insect maturity, the x-ray film was digitally scanned at 800 pixels/in. (Expression 1680, Epson America, Long Beach, Calif.), and the larval cross-sectional area was measured in an image-editing program (Adobe Photoshop LE 5.0, Adobe Systems, San Jose, Calif.). Kernels were assigned to one of six categories, as listed below, based on the insect larval size and insect morphology:

- Sound: no insect present
- Small larvae: larval area approximately 0.2 to 0.7 mm^2
- Medium larvae: larval area approximately 0.9 to 1.4 mm^2
- Large larvae: larval area approximately 1.6 to 2.8 mm^2
- Pupae: pupae area approximately 1.6 mm^2 or larger with limbs, snout, or wing features visible
- Emerged: exit hole of insect visible from exterior of kernel.

For rice weevils, the small larvae approximately corresponds to the first and second larval instar maturity stage, while the medium and large larvae correspond to the third and fourth larval instar stages, respectively (Kirkpatrick and Wilbur, 1965). In all life stages, the lesser grain borer is smaller than the rice weevil. Thus, within each size category, lesser grain borers are likely more mature than the rice weevils, and so the categories of small, medium, and large larvae would likely refer to a more mature insect for lesser grain borer than rice weevil.

For the live insect detection study, kernels were processed within 24 h after maturity estimation. For the dead insect detection study, infested and sound kernels were held at -8°C for five days to kill the insects, then stored at room temperature for approximately three months to allow the kernel MC to equilibrate, before processing in the SKCS 4100. The numbers of kernels collected for the live and dead insect detection studies, from all combinations of insect and wheat classes, are listed in tables 1 and 2, respectively. The dead insect study did not include small or medium larvae infestations because preliminary work showed the detection accuracy for these larval maturity levels was very low.

Conductance and Force Measurement

After insect maturity was estimated, kernels were processed with the SKCS. The weight, MC, hardness, and diameter measurements that the SKCS automatically computes were saved for analysis. Additionally, the SKCS software was set to save the conductance and force signals of each kernel for off-line analysis. The SKCS digitizes the voltage across the kernel at a rate of 4000 Hz while the kernel is being crushed, but only every fifth data point is actually stored. Data acquisition is triggered by the compression

Table 1. Number of kernels used from each insect – wheat class combination for live insect detection experiment.

Insect Maturity	Rice Weevil - HRW[a]	Rice Weevil - SRW	Lesser Grain Borer - HRW	Lesser Grain Borer - SRW
Small larvae	113	101	106	112
Medium larvae	111	101	103	104
Large larvae	122	110	105	125
Pupae	113	109	106	129
Sound	343	352	350	340

[a] HRW = Hard Red Winter Wheat; SRW = Soft Red Winter Wheat.

Table 2. Number of kernels used from each insect - wheat class combination for dead insect detection experiment.

Insect Maturity	Rice Weevil - HRW[a]	Rice Weevil - SRW	Lesser Grain Borer - HRW	Lesser Grain Borer - SRW
Large larvae	73	93	105	111
Pupae	131	133	115	126
Emerged	141	134	141	134
Sound	316	392	375	375

[a] HRW = Hard Red Winter Wheat; SRW = Soft Red Winter Wheat.

force exceeding a factory-set threshold. A kernel remains between the crescent and rotor of the SKCS for approximately 150 ms while it is crushed, so each conductance signal contained 135 to 140 points. The force is digitized at 4000 Hz, and every point is saved, so each profile had approximately 675 to 700 points.

For the live insect study, the MC of the sound kernels removed from the insect rearing jars averaged 12.0%, as computed by the SKCS. For the dead insect study, the kernels averaged 10.9% MC at the time of processing, as computed by the SKCS. After processing half of these kernels, the other half were tempered up to an average 13.0% MC before processing in the SKCS. Kernels at these two MCs were studied to determine the effect of varied MC on the force signals for detecting kernels with dead infestations.

Processing of Conductance Signals for Live Insect Detection

Figure 1 displays typical conductance signals acquired in this study for infested and un-infested kernels of various MC. In the SKCS, a kernel acts as one resistor in a two-resistor voltage divider circuit (Martin et al., 1993). Conductance is monitored by measuring the voltage across the kernel. A low-voltage measurement corresponds to low-kernel resistance, which is typical of high-MC kernels. If a live insect is present inside a kernel, there will likely be a large downward slope in the conductance signal, as shown in figure 1. This rapid voltage drop is probably caused by high-moisture insect parts and fluid (hemolymph) coming into contact with the crushing rotor or crescent and drastically lowering its resistance. Occasionally, a dry non-infested kernel will have a sharp peak in its conductance signal that will include a downward slope of similar magnitude caused by insects. However, these slopes always occur at levels greater than the initial voltage level across the kernel. This signal characteristic is shown in figure 1, which displays typical conductance signals from several types of kernels. Furthermore, the range of voltage levels in the conductance signal, when computed as the difference between the initial voltage level and the minimum voltage level, will be low for sound kernels of all MC levels and much higher for kernels infested with insects. Thus, a program was written to read all stored conductance signals, and compute the maximum downward gradient value and the range of voltages. Gradient was computed using equation 1 and voltage range computed using equation 2.

$$\text{Gradient} = \begin{cases} V_x - V_{x+1} \text{ if } V_x < V_0 \\ 0 \text{ if } V_x \geq V_0 \end{cases} \quad (1)$$

$$\text{Range} = V_0 - V_{min} \quad (2)$$

V_0 and V_{min} are the initial and minimum voltages measured across the kernel, respectively. V_x, V_{x+1} are the voltages of sampled points x and x+1, respectively. When V_x was greater than V_o, the gradient values were set to zero since these gradients were due to peaks in the conductance signal from dry kernels.

Processing of Force Signals for Dead and Emerged Insect Detection

Figure 2 displays typical force signals acquired in this study for infested and un-infested HRW and SRW wheat

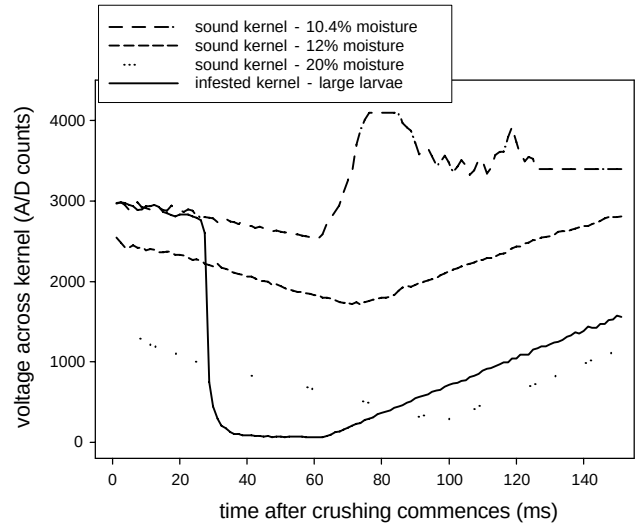

Figure 1. Typical conductance signals obtained in this study as kernels are being crushed in the SKCS 4100.

kernels. The duration of each crush force signal was highly variable, mostly due to differences in kernel size. To reduce this variability, all force signals were scaled to 128 points by fitting the original data to a fourth order, 9-point Savitzky-Golay smoothing filter (Press et al., 1992) and using this mathematical fit to estimate the force magnitude of the scaled signal at each of 128 equally spaced points. This processing gave some consistency in location of peaks among all force signals. If a dead insect was present inside the kernel, or if the insect had emerged from the kernel, the magnitude of the first peak, and upward slope to the first peak, tended to be less than if the kernel was not infested. The slopes and magnitudes of the force signals are quite different for SRW and HRW; however, differences in force signals for sound and insect infested kernels can be seen within each wheat class. The first peak always occurred in the first 40 points of the scaled force signal and most of the useful features for distinguishing insect-infested kernels from non-infested kernels were found in the first 40 points.

To detect insect-infested kernels, the following three features were extracted from the first 40 points in the scaled force signal: maximum upward gradient (as computed by

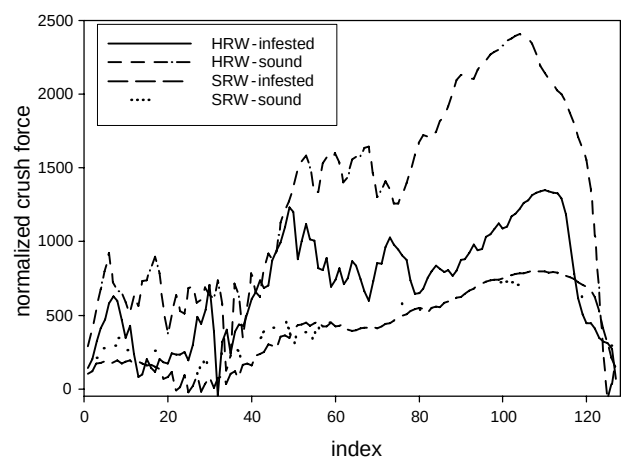

Figure 2. Typical crush force signals obtained in this study as kernels are being crushed in the SKCS 4100.

eq. 3), maximum downward gradient, and maximum crush force.

$$\text{Crush force gradient} = F_{x-1} - F_{x+1} \quad (3)$$

F_{x-1} and F_{x+1} are the crush force magnitudes at points x-1 and x+1, in analog to digital (A/D) counts.

The integration value for every point, from its location to the start of the signal, was saved for a total of 128 features of this type. The scaled signal was also further smoothed by an 11-point box-car moving average filter. All points in the smoothed averaged signal were saved as potential features. In addition, parameters normally computed for each kernel by the SKCS were used as potential discriminating features. These parameters include: maximum crush force in the entire signal, kernel weight, kernel diameter, MC, and hardness index (Martin et al., 1993). A total of 264 features were extracted from each force signal.

Discriminant analysis was used as the classification procedure (Huberty, 1994). Features used to perform classifications were selected by performing an exhaustive search, using all possible combinations of one, two, three, and four individual features from the 264 feature data set. Classification using both pooled and non-pooled covariance matrices were tested. The Mahalanobis distances were computed from each kernel to the insect-infested and sound kernel groups. A kernel was classified into the group with the lowest corresponding Mahalanobis distance. To minimize the number of false positive errors, the *prior* probabilities for infested and sound kernels were set at 5% and 95%, respectively. The sample means and covariance matrices for each group were computed using half of the samples, randomly selected. The feature set that obtained the lowest classification error rate on the other half of the samples was recorded. This procedure was run separately for HRW and SRW samples to obtain optimal classification accuracies for each class.

Additional Sample Sets for False Positive Testing

In addition to the sound kernels picked out from the insect colonies, a total of 12,900 SRW and 14,400 HRW kernels, of various varieties, were collected from commercial farms shortly after the 2001 and 2002 harvests so they could be assured of not containing any internal infestations. These kernels were run in the SKCS in sets of 300 (43 sets for SRW and 48 sets for HRW), as is the normal operating procedure for the SKCS. The SRW kernels came from either Missouri or Arkansas and the HRW kernels came from either Kansas, Oklahoma, or Colorado. The MC of these samples ranged from 9.8% to 13.3% for SRW and 9.0% to 14.25% for HRW. The SRW varieties included 3235, Ernie, Madison, 9663, Pat, Roane, and Sisson. The HRW varieties included Pioneer 2137, 2163, 2174, Custer, Jagger, Karl, Millennium, Neeley, Proghorn, Rampart, and Wesley.

The effect of MC of sound kernels was tested by tempering sets of 25 HRW kernels and SRW kernels (unknown varieties) up to 14%, 16%, 18%, and 20% MC to determine if high MC decreased classification accuracy.

None of these additional samples were used in the development of the classification algorithms. They were only used for testing the final classifiers.

Results and Discussion

Classification of Live Insect Infestations from Conductance Signal Features

Figure 3 displays a scatter plot of all maximum gradient values and voltage ranges in the conductance signals from all kernels removed from the rearing jars. The ellipse with a solid boundary is a 99.90% prediction interval for sound kernels of all MCs. Since it is important to minimize false-positive errors (sound kernels classified as infested), a 99.99% prediction ellipse was computed and all data points falling outside this ellipse were classified as insect infested. As such, a false-positive classification error of 0.01% can be expected with this method. There were two false-positive errors made when this classification scheme was applied to the 27,300 sound kernels not used in the classification algorithm development, a 0.01% false positive error rate. Live insect detection results for each insect–wheat class combination are shown in figure 4. Higher classification accuracy is obtained for more mature insects. This result is expected given that insect size increases with maturity. Average classification accuracy for all infested kernels from both wheat classes were 24.5% for small larvae, 62.2% for medium larvae, 87.5% for large larvae, and 88.4% for pupae. The best classification results were obtained for HRW infested with rice weevils. Generally, HRW had better classification results than SRW, and more rice weevil infestations were detected than lesser grain borer infestations. Rice weevils are a larger insect than lesser grain borers, thus insect or tunnel size may have been a factor in their higher detection rate. Additionally, HRW may break apart more suddenly than SRW, causing insect hemolymph to contact the SKCS rotor or crescent more abruptly, leading to larger gradients in the conductance signals. However, more study would be needed to confirm whether the differences in detection accuracies between wheat classes and insect species are indeed significant. Analysis of variance of the means of kernels infested with insects at each maturity level and sound kernels found that wheat class, kernel MC, and insect species did not cause any of the means for maximum gradient or voltage range to be significantly different at the 95% confidence interval. Means of tempered sound kernels with high MCs were not significantly different than means of sound kernels that were pulled from the incubation jars. Only insect maturity caused significantly different means. In all cases, kernels infested with insects beyond the small larval stage had significantly different means than sound kernels at the 95% confidence interval. Kernels infested with small larvae did not have significantly different means than sound kernels at the 95% confidence interval.

The low of a false positive rate with this method indicates that for 300 kernel samples, only 3% would have one false positive kernel and only 0.04% would have two false positives kernels (assuming a Poisson distribution of false positive errors). Thus, if one kernel in a 300 kernel sample is classified as insect infested, one can be 97% confident that it is in fact due to a kernel infested with a live insect.

Classification of Dead or Emerged Insect Infestations from Force Signal Features

Similar features were selected to detect insect infestations using force signals in HRW and SRW. The discrimination features chosen are listed below:

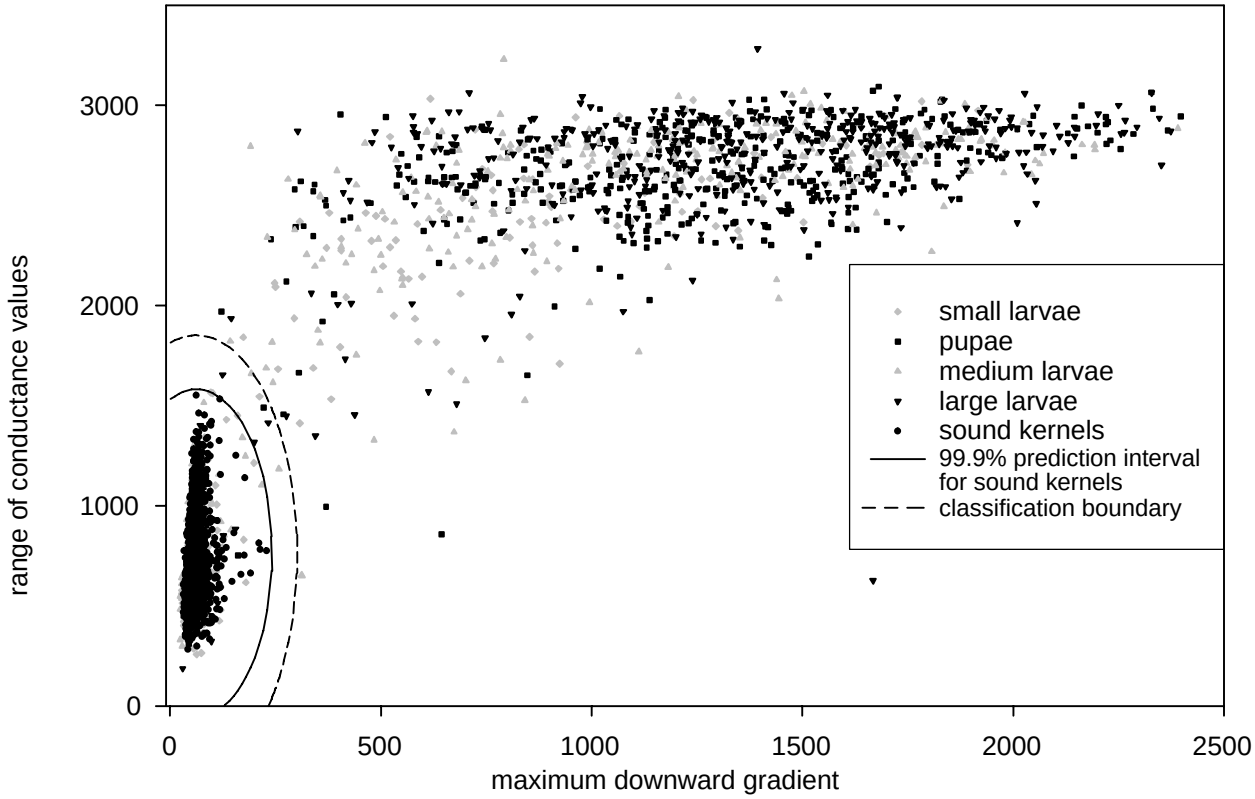

Figure 3. Scatter plot of maximum downward gradient and range of vol ages in conductance signals from all kernels.

- HRW: maximum upward slope in first 40 data points, integration of the first 20 points, and 10th point of the box-car averaged signal.
- SRW: maximum upward slope in first 40 data points, and 10th point of the box-car averaged signal

All these features are associated with the energy required to first crack the wheat kernel. This energy is less for infested kernels than uninfested kernels. Inclusion of parameters that are normally computed by the SKCS (i.e. kernel weight, hardness, moisture, diameter), were not found to improve classification results. Unpublished results indicate that if the diameter and weight measurements were more precise, then they would be very helpful for classification of infested kernels. For both SRW and HRW wheat, discriminant functions with non-pooled covariance matrices gave better classification accuracies than functions using pooled covariance matrices.

The overall classification accuracies for HRW were 41% for large larvae, 46% for pupae, 67% for emerged infestations, and 99.4% for the sound kernels pulled from the rearing

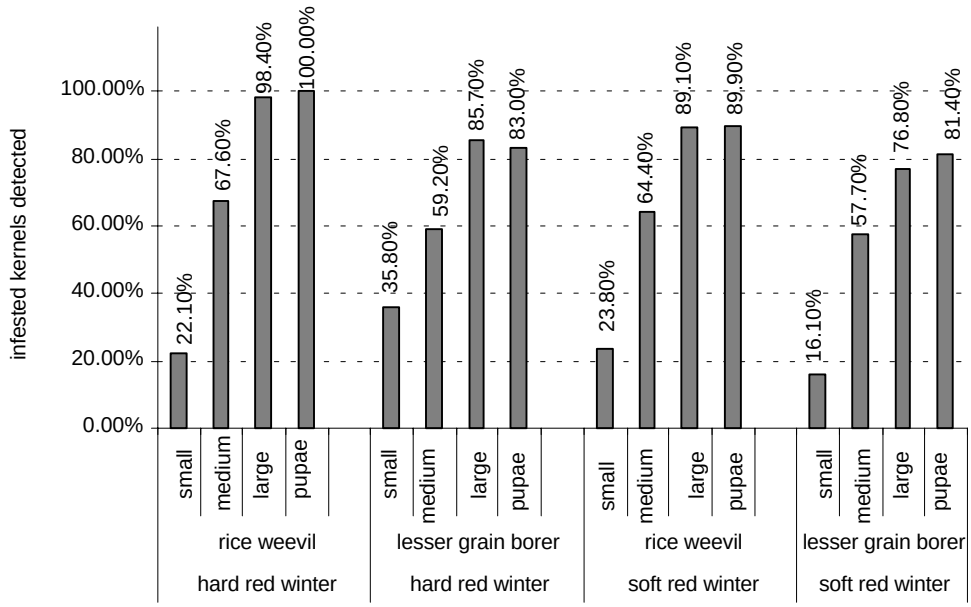

Figure 4. Classification results for live insects by conductance signal processing from all insect maturity, insect species, and wheat class combinations.

jars. Overall classification accuracies for SRW were 78% for large larvae, 83% for pupae, 78% for emerged infestations, and 99.9% for sound kernels pulled from the rearing jars. Figure 5 shows the insect-infested kernel detection rates for both HRW and SRW wheat classes, each insect, and all maturity levels. As can be seen from figure 5, dead and emerged insect detection rates are higher for SRW than HRW and detection rates were higher for rice weevil than lesser grain borer. Insect maturity does not appear to affect insect detection rates in SRW as much as they do in HRW. This finding might be due to more gradual breakage of the kernel in SRW, which might also explain the overall higher detection rates for SRW. Moisture content of sound kernels did not appear to affect false positive error rates when MC was below 14%. However, false positive errors increased for kernel MCs above 14%. Of the tempered kernels elevated to high MC, there were no false positive errors for the 14% MC kernels but false positive errors for 16% MC kernels increased to 36% for SRW and 4% for HRW. False positive errors for the 18% and 20% MC kernels were 36% and 76% for SRW, respectively; and 20% and 60% for HRW, respectively. Fortunately, these errors should not be a problem for properly stored grain where the MC is generally below 13.5% (Christensen and Sauer, 1982).

All results reported are based on *prior* probabilities (probability of infestation in a random sample) of 5% for insect infestation and 95% for sound kernels. Figures 6 and 7 display response operating curves to show the effect of different *prior* probabilities on classification results. False negative error rates for both SRW and HRW rise very rapidly for insect *prior* probabilities below 5%, with little improvement in false positive error rates. Raising the *prior* probabilities of insect infestation from 5% to 10% does greatly improve recognition of insect damage in HRW but also greatly increases false positive errors.

The SRW discriminant function can be used for cases where wheat classes are mixed. The false positive error rate for HRW classified by the SRW calibration was 0.1%. The detection rate of infested HRW kernels when using the SRW calibration is reduced, however. Overall classification accuracies for HRW when using the SRW discriminant function were 20% for large larvae, 36% for pupae, and 57% for emerged infestations. If the HRW algorithm is used for SRW, the false positive error rate would be greater than 5%, as many uninfested SRW kernels have similar force signals as infested HRW kernels.

Low false positive error rates are required to estimate insect infestations in wheat. The USDA limit of 32 infested kernels in a 100-g sample (approximately 3000 kernels) corresponds to an infestation rate of slightly over 1%, or three kernels within a 300-kernel sample. In order to have a chance at estimating infestation levels, the false positive detection rates need to be much lower than the incidence rate for the defect to be detected. Otherwise, inspection of very large samples would be required. Using the developed algorithms, false positive error rates for the 12,900 SRW and 14,400 HRW kernels, which were not included in the discriminant analysis training, were 0.17% for SRW and 0.51% for HRW. The average number of false positive kernels for all 300 HRW kernel samples sets was 1.5 kernels with a standard deviation of 1.69 kernels. From this data, it can be expected that 95% of all 300-kernel sets would have less than or equal to five sound kernels classified as insect infested and 99% of all 300-kernel sets should have less than or equal to seven false positive kernels. For SRW, 95% of all 300-kernel sets should have less than or equal to two false positive kernels and 99% should have less than or equal to three false positive kernels. This result indicates that detection of insect infested samples at or below 32 infested kernels per 100 g is possible with a 300-kernel sample for SRW but a larger sample would give better confidence in the result, and a larger sample would be necessary for HRW. Analysis of variance found that there were no significant differences, at the 95% confidence level, in mean error rates for different varieties, year of harvest, MC, or hardness of these kernels.

Classification results obtained from the SKCS data compare favorably with x-ray imaging and near-infrared spectroscopy methods used to detect internal insects. Human examination of x-ray films is a more accurate method of

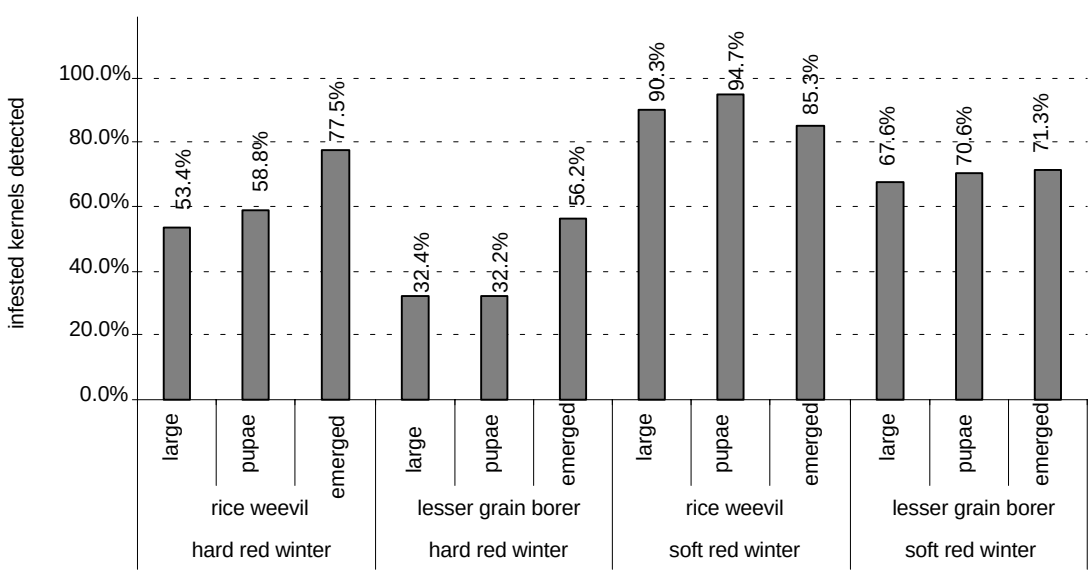

Figure 5. Classification results for dead and emerged insects by force signal processing from all insect maturity, insect species, and wheat class combinations.

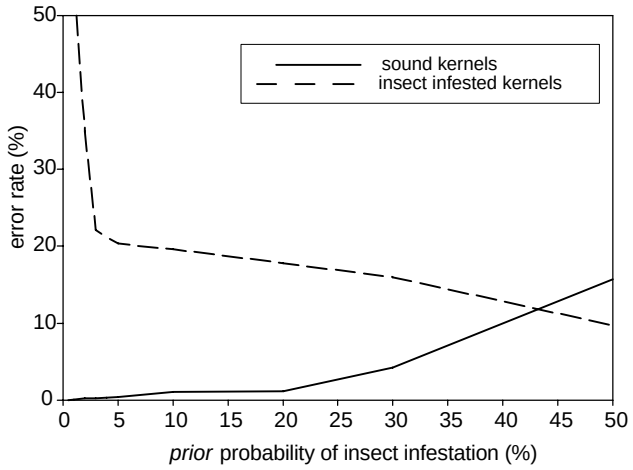

Figure 6. Classification response operating curve for soft red winter wheat (SRW).

detecting infested kernels at all maturity levels but can have false-positive errors of 1.0% or higher (Haff, 2001). Computer algorithms to automatically scan x-ray images have similar recognition rates as the SKCS for insect-infested kernels but have higher false-positive rates, about 7.4% (Haff, 2001). Near-infrared spectroscopy methods also suffer from false positive errors and, additionally, kernel orientation problems (Ghaedian and Wehling, 1997). Both x-ray imaging and near-infrared spectroscopy methods have the advantage that they are non-destructive. However, the false positive error rates using these other technologies would require the use of very large sample sizes for detection of low incidence levels of insect-infested kernels.

Conclusion

The method developed for detecting wheat kernels with internal insects appears to be very accurate for kernels infested with live insects at the large larvae or pupal stages. Detection accuracy for live infestations averaged 88% for large larvae and pupal stages with the false positive error rate at 0.01%. This method should be useful for detecting live infestations in commercial samples where the rate of infestation is as low as 1 kernel in 300, or 10 kernels in a 100-g sample. The method for detecting dead insect infestations is moderately accurate for kernels infested with dead or emerged insects. Implementation of the method does not require any hardware changes to the SKCS, just additional software to process the conductance and force signals. While insect detection rates of the method are not as high as inspection of x-ray films with a magnifying glass, it is rapid and comparable to, or better than, existing automatic detection methods and does not suffer from high false-positive results. This finding holds true for inspection of wheat under all reasonable MC.

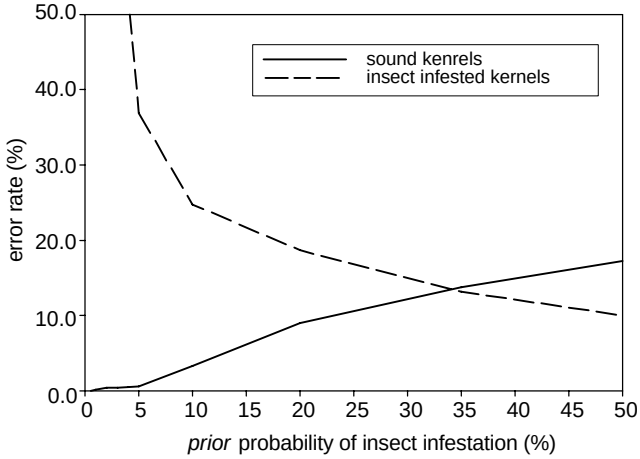

Figure 7. Classification response operating curve for hard red winter wheat (HRW).

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