Identification of insect damaged wheat kernels using transmittance images

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Transmittance images of wheat kernels are used to classify insect damaged and undamaged wheat kernels. The histogram of pixel intensities of the wheat images were used as the features. Combination of the linear model and a radial basis function network in a committee resulted in a false positive rate of 0.1 at the true positive rate of 0.8 and an area under the receiver operating characteristics curve of 0.92.

Introduction: Infested wheat kernels cause loss of quality in wheat products. They cause a lot more damage if they are put into storage with other kernels. It is important to be able to identify insect damaged kernels to reach proper decisions about them.

Current methods of insect detection such as cracking and flotation [1], infrared CO_2 analysis [2], immunological methods [3], NIR [4], and X-ray inspection [5] can be laborious, slow, expensive, and ineffective at distinguishing a sound kernel from a kernel that is internally infested. It is possible that impact acoustics [6] may be used to detect insect damaged kernels as an alternative method. In this Letter we describe a method to identify insect damaged kernels based on transmittance images. This method is fast and inexpensive compared with the other methods. Recently, reflection images of kernels was used for identification of different types of grains [7].

In our method, the colour histogram of pixel intensities is first estimated for each kernel image. Then the colour histogram based feature vector is used in a number of different algorithms, namely the linear model, quadratic model, K-nearest neighbour, linear model with weight decay and radial basic function (RBF) network for classification.

Wheat images and features: Hard red winter wheat (H2) was used to obtain the images shown in Fig. 1. The insect damaged kernel images were taken from wheat infested with rice weevil and kept at a moisture of about 11%. Transmittance images of wheat were sampled at 800 pixels/inch. We used 355 good and 364 insect damaged kernels in our experimental study.

Fig. 1 *Sample of good and insect damaged kernel pictures*

The histogram of the red component of the pixels colours over each wheat image was used as the input feature for the learning algorithm because red is the dominant colour. The 256 different red components were put into bins as follows. If the red value was less than or equal to 80 the pixel was added into bin 0. If it was larger than 250 it was added into the last bin. Otherwise, the pixel was added into a bin in-between, each bin being responsible for five different red values resulting in a total of 36 input features. Since the bins with red value less than 80 were almost always empty, we chose to put all pixels with a red component of less than 80 into one bin. We assigned output 0 to the good kernels and 1 to the insect damaged kernels in the classifier.

In addition to the histogram features, we tried two other features: the minimum, the maximum and majority over 3×3 rectangles and the mean on the centre of the wheat. We also tried using, in addition to the red histogram, mean of red, green and blue, hue, saturation, brightness and mean x and y of CIExy. However, the results did not improve.

Learning algorithms: We used two examplar-based algorithms: K-nearest neighbour and radial basis function (RBF) network, as well as two model-based algorithms: linear and quadratic models. To see if regularisa-tion would help with the linear model, we also tried weight decay. The input features for all the algorithms were $\underline{x} \in \mathcal{R}^{36}$ and the corresponding outputs were $y \in \{-1, 1\}$. The inputs were normalised to have sample mean 0 and standard deviation 1 for each input dimension on the training set.

To obtain reliable figures on algorithm performance, we used cross-validation. We randomly partitioned all the available data into a training and a test set. The training set used 90% of data from each class and the test set used the remaining 10%. We repeated the partitioning 10 times.

We estimated the model performance using the receiver operating characteristics (ROC) [8] and the area under the ROC curve (AUC) [9] on the test set. To obtain different false and true positive rates on the ROC curve, we varied the threshold of each learning algorithm.

Linear model: Let $A_{N \times (36+1)}$ contain training inputs preceded by 1 and $\underline{b}_{N \times 1}$ contain the outputs y_i for all the N training examples. The linear model is obtained by solving for $\underline{w}_{37 \times 1}$ in the equation $A\underline{w} = \underline{b}$. To solve this equation we need to invert $A^T A$. Since A was not full rank, $A^T A$ was not invertible. We used singular value decomposition with $\epsilon = 0.001$. If the output for a test case was smaller than a certain threshold we classified it as good and otherwise we classified it as insect damaged. Each threshold for the linear classifier corresponds to a point on the ROC curve (i.e. a certain FP and TP rate). To obtain different points on the ROC curve, we varied the threshold for the output from -2 to 2 in steps of 0.1. For a certain threshold t and for a certain input, if the output of the linear model was more than the threshold, the input was classified as insect damaged, otherwise it was classified as good. When we varied the threshold between -2 to 2 we were able to draw the complete ROC curve, that starts at TP and FP rates of 0 and ends at TP and FP rates of 1.

Radial basis function (RBF) network: We used the RBF network for choosing the first layer weights step-wise as the training example with the worst training error. We used 20 basis units. The RBF network's first layer performs a nonlinear transformation of the inputs and then the output is determined as a linear combination of the basis function outputs. We used thresholds as in the linear model to obtain different ROC curve points.

Linear model and RBF network committee: We used a linear combination of the RBF network and the linear model outputs as the output of the committee and the same thresholds to obtain ROC curve points.

Quadratic model: We used the inputs used for the linear model and also the multiplication of each input with another input. We used thresholds as in the linear model to obtain different ROC curve points.

K-nearest neighbour: This algorithm needs to store all training data. To classify a new data point, first the K closest data points (K neighbours) in training data are determined. The new data point is classified as positive or negative, based on the count of positive and negative count in the K neighbours. The number K determines the smoothness of the K-nearest neighbour classifier. As K increases the classifier does a smoother inter-polation. We used 5, 10, 15 and 20 as the values of K in our experiments. To obtain different points in the ROC curve, we varied the threshold for the output from 0 to 1. We computed the mean of the labels of the K-nearest neighbours. If the mean is less than the threshold, we classify a test case as good and otherwise as insect damaged.

Linear model with weight decay: Weight decay, ridge regression and shrinkage aim at reducing the weights and hence obtaining simple models that do not overfit the training data. The weight decay solution is $\underline{w}^* = (A^T A + \lambda I)^{-1} A^T \underline{y}$. The selection of the weight decay parameter λ is very important. If λ is very small, the weight decay does not change the solution; if it is too large, the solution gets smaller in size at the expense of bad fit to the data. We used thresholds as in the linear model to obtain different ROC curve points.

Results: For each of the 10 training-test set partitioning of the available data, we used the training set to train the learning algorithm. We then used the test set to compute the ROC curve for each partitioning.

We interpolated the ROC curve for each partitioning and reported the mean and standard deviation of the true positive rate (sensitivity) for

each false positive rate (1-specificity) value for each learning algorithm [8]. The mean and the standard deviation on the ROC curve gives us a better idea of the performance of an algorithm. To obtain a reliable mean, we discarded the ROC curve with the maximum and minimum AUC and computed the average ROC curve using the eight remaining ROC curves. Results are summarised in Table 1 and Fig. 2, in which the ROC curve of only the linear model, the RBF network, and the RBF network and the linear model in committee is shown. Because of its simplicity and performance the linear model seems to be the best single algorithm. The nearest neighbour was the worst algorithm, regardless of the K of the nearest neighbour. The RBF and linear model committee performed the best. Combining the linear model and a radial basis function network in a committee resulted in an FP rate of 0.1 at the TP rate of 0.8 and an AUC of 0.92. Some of the wheat images that our algorithms failed to distinguish were not distinguishable by a human expert either.

Table 1: Area under ROC curve (AUC) for different learning algorithms

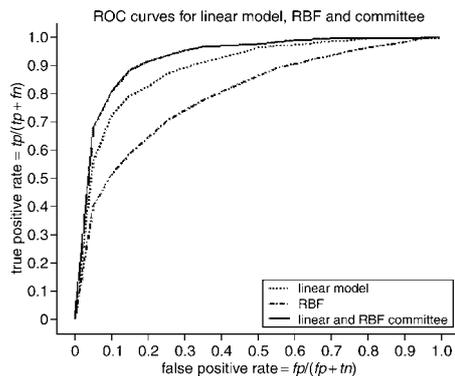| Algorithm	AUC
Linear	0.86 ± 0.03
RBF	0.79 ± 0.05
RBF and linear committee	0.92 ± 0.03
Quadratic	0.85 ± 0.05
5 nearest neighbour	0.55 ± 0.02
10 nearest neighbour	0.77 ± 0.04
15 nearest neighbour	0.79 ± 0.03
20 nearest neighbour	0.76 ± 0.03
Weight decay $\lambda = 0.002$	0.86 ± 0.02
Weight decay $\lambda = 0.003$	0.87 ± 0.02
Weight decay $\lambda = 0.004$	0.84 ± 0.02

Fig. 2 *Performance of different learning algorithms*

Additional information about the kernels such as reflectance images, compression force, conductance measurements, and impact sounds [6] can be used to improve performance leading to a multiple sensor insect damaged wheat kernel classifier system.

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