Automated Classification of Wrinkle Levels in Seed Coat Using Relevance Vector Machine

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***Abstract*—Seed-coat wrinkling in soybean is often observed when seeds are produced in adverse environmental conditions and it has been associated with low germinability. Manually rating seeds is time consuming, error prone and fatiguing – leading to even more errors. In this paper, an automated approach for the rating of seed-coat wrinkling using computer vision and machine learning algorithms is presented. The proposed system provides a GUI for ground truth annotation and a pipeline consisting of seed segmentation, feature extraction and classification using multi-class Relevance Vector Machines (mRVM). This research also proposes a reliable new feature for seed-coat rating based on texture. An additional contribution of this paper is a database of annotated seed images, which is being made available to researchers in the field. The results showed an accuracy in wrinkling rating of 86% for matches within ± 1 scores from the ground truth.**

I. Introduction

Characterization of soybean [Glycine max (L.) Merr.] seed coat can provide information about seed quality [1, 2]. For example, lignin content, hilum, strophiole, and the overall structure of the seed coat given by porosity, color, etc have been associated with a seed's susceptibility to mechanical damage, longevity, tolerance to field weathering, performance, permeability, resistance to shrinking and fungal infection, and so on [3–6]. In that sense, seed-coat wrinkling can provide relevant information regarding seed quality, including germinability and usability [7–9]. While seed-coat wrinkling is under genetic control, environmental conditions such as alternating periods of wet and dry conditions and exposure of seeds to high temperatures during seed development and maturity are recognized as major reasons for seed shriveling and coat wrinkling [5, 10, 11]. Therefore, understanding the association between seed-coat wrinkling and seed performance will be useful for the development of genotypes with improved seed quality.

Today, experts visually rate seed-coat wrinkling using an index that ranges from zero (no visible wrinkles) to nine (highly wrinkled) [1, 8, 12–14]. This approach is time consuming, subjective, and heavily dependent on an individual's experience and focus. Therefore, a reliable, consistent and automated approach that eliminates the subjectivity of a visual rating system would be of great benefit.

Technology is playing an increasing role in today's agriculture [15], and state-of-the-art machine learning and image processing techniques have great potential for further applications in agriculture, including for the assessment of seed-coat characteristics. In fact, machine vision, robotic platforms, and environmental sensors are examples of engineering methods with applications in agriculture [16]. Machine vision technology for instance brings non-destructive, high-throughput and accurate solutions to many problems including seed assessment [17, 18]. In that respect, Shahin and Symons [19] introduced an image-based approach to measure seed size, reducing the time for seed sizing by a factor of 20. Automation of seed vigor assessment has been proposed by Sako et al. [20], by using an inverted flatbed scanner to capture digital images of germinating seedlings, and quantitatively evaluating the quality of the seed lot through image analysis.

Machine learning algorithms are widely used to assess plant and seed characteristics. Yao et al. [21] applied Support Vector Machines (SVM) to rice diseases detection. They used shape and texture features to accurately classify three different rice diseases: rice bacterial leaf blight, rice sheath blight and rice blast. Finally, combining machine learning and image processing is the certain solution for achieving even higher and more precise automation in seed assessment [22–25]. In that sense, extracting features from different color spaces like RGB, HSV, and Lab often gives a good class separability for the classifiers, and combining color and texture is also widely used for classification and seed assessment. However, classification results can be affected by uncertainty in light conditions such as reflection and shadowing. Therefore, an image capturing device was designed in [26] to control light conditions. In that case, it was proposed a color/texture-based classifier to detect ten categories of defects in corn seeds. The system employed color histograms in RGB and HSV, Gray level co-occurrence matrices (GLCM), and Local Binary Patterns (LBP) as features for classification. However, since the visible spectrum is not always informative, Wang et al. took a step further by using Near-Infrared (NIR) spectrometry and Neural Networks (NN) to classify healthy and fungal-damaged soybean seeds [27, 28].

In this paper, we present an automatic rating system

978-1-5386-1235-4/17/$31.00

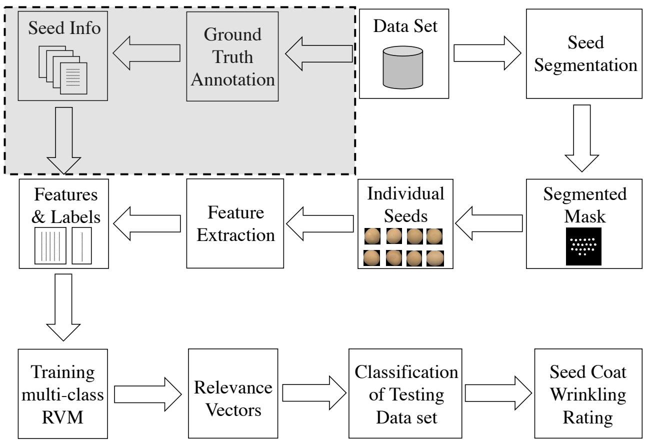
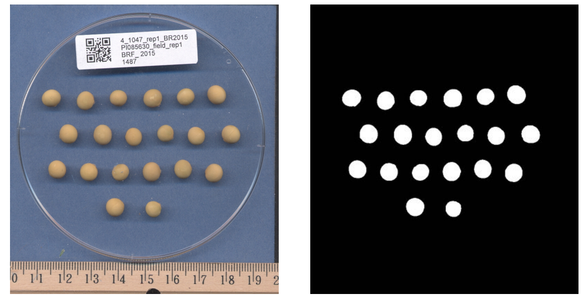
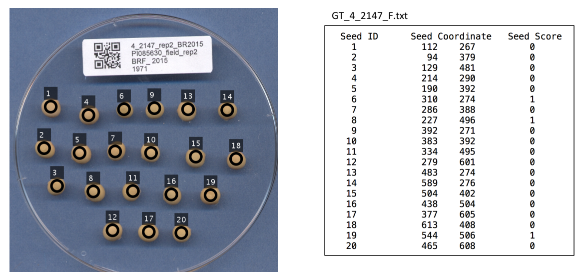


Fig. 1. Seed coat wrinkling rating pipeline



(a) (b)

Fig. 2. Sample image from dataset (a) original RGB image, (b) segmented binary image



GT_4_2147_F.txt

Seed ID	Seed Coordinate		Seed Score
1	112	267	0
2	94	379	0
3	129	481	0
4	214	290	0
5	190	392	0
6	310	274	1
7	286	388	0
8	227	496	1
9	392	271	0
10	383	392	0
11	334	495	0
12	279	601	0
13	483	274	0
14	589	276	0
15	504	402	0
16	438	504	0
17	377	605	0
18	613	408	0
19	544	506	1
20	465	608	0

(a) (b)

Fig. 3. GT-SeedExtractor GUI for seed annotation and labeling. (a) annotation of source image, (b) ground truth information exported by GUI

for seed-coat wrinkling. The proposed system uses image processing and machine learning techniques for classifying both individual seeds and the sets of seeds. The proposed pipeline consists of: a GUI for ground truth annotation; a seed segmentation algorithm; feature extraction; and finally classification using multi-class Relevance Vector Machines (mRVM). The segmentation algorithm uses K-Means on the Lab-color space, while morphological operation is applied to improve the foreground masks. This paper also proposes a new metric based on a texture feature to characterize seed-coat wrinkling. Also, while a proposed second metric based on a shape feature did not prove as helpful, our experiments indicated that further investigation on that feature could help classifying different genotypes of soybean. In the following sections, first, an overview of the challenges in seed-coat-wrinkling rating is provided. Next, we introduce the automatic pipeline for rating seed-coat wrinkling. Then, results for the proposed system are presented and discussed.

II. Seed Coat Wrinkling Rating Overview

Figure 1 shows the proposed pipeline to grade seeds based on the level of seed coat wrinkling. A software for ground truth annotation was also developed and utilized by three experts, providing information on the seed characteristics that was used in the proposed pipeline. The pipeline starts with seed segmentation and the extraction of individual seeds, which are followed by feature extraction. The mRVM is then trained using these automatically extracted features and the annotated labels, and the system is tested using different testing datasets.

A. Dataset

The dataset[1] used in this paper consisted of 150 images of seeds with different levels of seed coat wrinkling. Seeds depicted in the various images below were collected from greenhouse and field experiments conducted in 2014 and 2015. Soybean genotypes included plant introductions – Maturity Group III (MG III), and some parental lines of the Soybean Nested Association Mapping (NAM) populations. Figure 2(a) is a sample image of such seeds, in this case with the lowest seed coat wrinkling rating in the dataset. All images were taken with an Epson Perfection 1200U scanner in an image capturing station system that controlled light conditions at the same level across all images. The entire dataset consists of 3415 individual seeds, which were rated (annotated) by three experts.

[1]The dataset is available for downloanding at http://vigir.missouri.edu/Research/seed_dataset

B. Annotation and Labeling

A Graphical User Interface (GUI) was designed for rating of seed-coat wrinkling by plant biologists. The GUI provides an interactive environment for users to select each seed from the image, rate them based on their level of wrinkling, and export the both individual and group information. Examples of an annotated image (a) and information exported by the GUI (b) are shown in Figure 3.

In this research, seeds in the images were labeled by three independent plant biologists to minimize the rating bias associated with an individual. Table I illustrates images of individual seeds segmented and then cropped from the original image. The same table also shows the numbers of seeds rated by each expert per seed-coat wrinkling score. Those scores range from zero (no visible wrinkles) to nine (highly wrinkled). Typical sample images per score (or rate) are provided for reference. (Table I). As it can be observed from Table I, the dataset contains in general fewer seeds with mid-range (3-6)

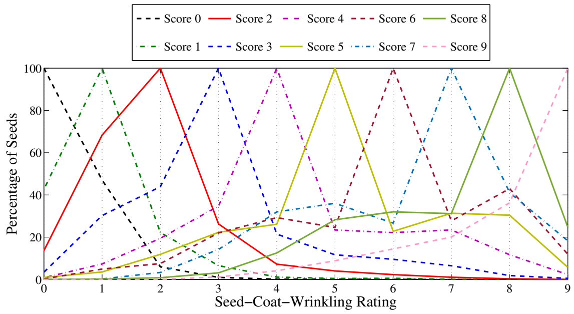


Fig. 4. Uncertainty of seed coat wrinkling rating by experts. Each line-color represents percentage of seeds rated differently comparing to the picked level.

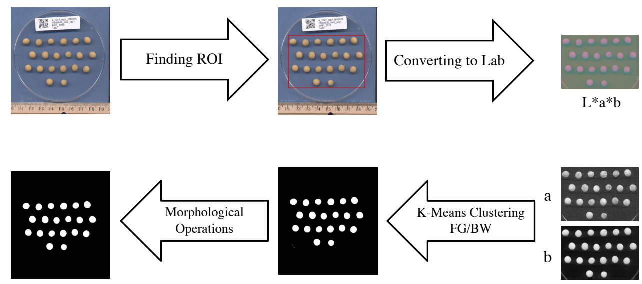


Fig. 5. Seed segmentation pipeline

and upper-range (7-9) wrinkling rates than low-range rates (1-2).

Figure 4 shows the uncertainty in the rating of seed-coat wrinkling by experts. Each colored line represents the percentage of seeds rated differently compared to the selected rate. For instance, for all seeds selected as rate 1 by one of the experts, 20% of the experts rated those seeds as level two and 40% as level zero (dotted green line). Based on the same Figure, we inferred from this uncertainty among experts that a range of ± 1 should be considered when referring to the ground truth. This inference seems reasonable for all rates even though the uncertainty towards the mid-range levels has an even greater range, and this fact would affect negatively the performance of our classification.

C. Seed Segmentation and Feature Extraction

As implied earlier, segmentation is widely used for plant characterization and seed assessment [17, 19–21, 23, 29]. Almost all segmentation algorithms are based on prior knowledge of the images under consideration [30–33]. Some times, this knowledge is in the form of the general shape of the object, properties of the background, lighting conditions, etc. In this paper, individual seeds were automatically segmented from the original images using simply color information.

Figure 5 shows the segmentation pipeline used in this paper. This segmentation process starts with finding the region of interest (ROI) surrounding the seeds. Next, the original RGB images are converted into the L*a*b color space [34]. The a and b channels – representing the red/green and yellow/blue aggregated colors respectively – are more distinctive color quantifier than simple RGB as they can more consistently segment foreground and background colors that are perceived under different illumination conditions. Therefore, as shown in Figure 5, the a and b channels were selected as features for a K-Means clustering algorithm for partitioning the image into background and foreground. After the clustering, morphological operations were applied to the resulting binarized image to obtain more homogeneous segments. Figure 2(b) illustrates in more detail one sample of such segmented images.

Once seeds are segmented, individual seeds can be automatically extracted and labeled for future correspondence with the annotations provided by the experts. Also, from the individual cropped images of the seeds, features were extracted and used for training of the multi-class Relevance Vector Machine (mRVM). Four features were studied here: Integrative Co-occurrence Matrices; Local Binary Patterns (LBP); Maximized SD; and Shape. While the first two features were previously introduced in [35] and have shown advantage over other commonly used features such as Gabor filter, Complex Wavelet Transform and Chromatic features, here we propose two new features as defined next.

Maximized SD (MaxSD): This newly proposed feature was extracted from the gray scale cropped images of individual seeds. It is defined as the maximum of the L2-norm of the standard deviation on the pixel values over a varying window size divided by the number of pixels in the window. That is,

$$MaxSD = \max_{i,j \in W} \left\{ \frac{\|\sigma(i,j,sz)\|}{N} \right\}$$

where $\sigma(i,j,sz)$ is the standard deviation for a window W with size $N = sz\, x\, sz$ and centered at pixel coordinates (i,j). It is important to mention that the size of the window is a function of its center (i,j) to avoid the effect of background pixels in $\sigma(i,j,sz)$. Figure 6 shows examples of $MaxSD$ for different window sizes. As the Figure indicates, $MaxSD$ captures the texture of the foreground (seed coat) by determining the point at which σ and N lead to a smooth image of the seed.

Empirical analysis of our experiments found that features that represent the structure of the texture ranter than the intensity of that texture did not work as reliably as the proposed $maxSD$. That is, our experiments showed that seeds with the same wrinkling rates may present different texture structure, but the same intensity of texturing, at the same time that seeds with different wrinkling rates may present the same texture structure, but different intensities of texturing. In that sense, $maxSD$ proved to be a better feature than other features in the literature. That is not to say that maxSD is a perfect feature, reason for which we also used other features in our experiments. In fact, while analyzing Figure 7), one will notice that even though the average values of $maxSD$ for each wrinkling rate are monotonically increasing with those same rates, their distribution are largely overlapped. This overlap is due to all variations in annotation (uncertainly among experts), to lighting conditions, perceived seed color by the sensors,

TABLE I
STATISTICS ON INDIVIDUAL SEEDS RATED BY THREE EXPERTS

Rates	0	1	2	3	4	5	6	7	8	9
Sample cropped Image										
# of seeds rated by expert 1	766	1162	348	156	96	92	137	188	303	167
# of seeds rated by expert 2	759	973	510	362	229	217	143	77	86	59
# of seeds rated by expert 3	1153	964	360	236	153	112	106	129	89	113

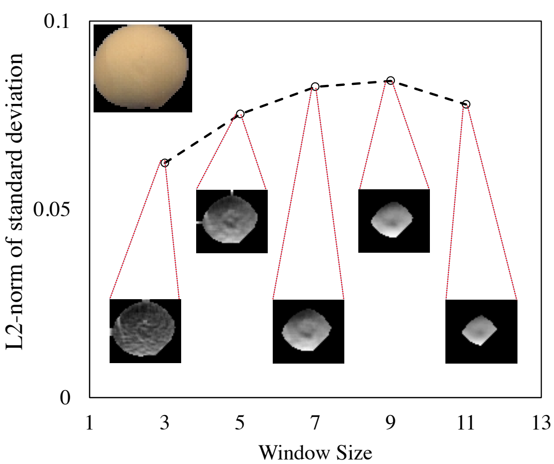


Fig. 6. L2-norm of local standard deviation for different window sizes

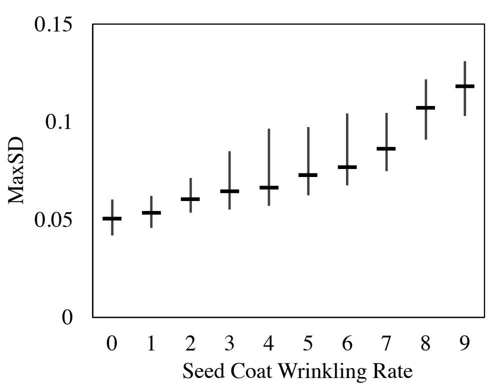


Fig. 7. Uncertainty of maxSD feature descriptor for different seed coat wrinkling levels

etc. However, in most cases, the feature was able to correctly capture the level of seed coat wrinkling. Later, we will show that together with other features, $maxSD$ provided a very good separability for the classifier.

Seed Shape: When we started this experiment, it was assumed that the shape of the seed could be another factor in determining the level of seed-coat wrinkling. That is, it was expected that seeds with smaller wrinkling scores would have more circular shapes than those with higher scores – as observed in the top row of Table I. Therefore, we investigated the use of eccentricity of an ellipse as a feature for detecting the correlation between seed shape and seed-coat wrinkling, that is:.

$Eccentricity = \frac{e_1}{e_2}$

where e_1 is the distance between the foci of the ellipse and e_2 is its major axis length (Figure 8).

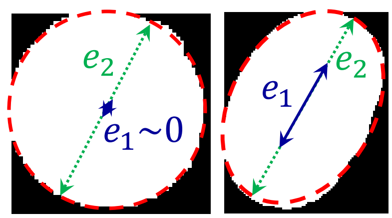


Fig. 8. Eccentricity of seed masks defined as the ratio of the distance between the foci and major axis length

The performance of this shape feature in characterizing seed-coat wrinkling was evaluated and the results are shown in Figure 9. As the Figure indicates, there was a very large overlap between the shape distributions for any two wrinkling levels. This fact rendered this feature quite uninformative, at least when applied to the entire dataset. So, we decided to further exam the dataset and inspect whether the shape was a function of its genotype. Figure 10 presents the variation of the average eccentricity per genotype and wrinkling score. As it can be observed, some genotypes – e.g. LD 015907 and PI 574486 – seem to present a higher correlation between their eccentricity and their wrinkling scores than the others. However, for the other four, the shape seems unaffected by the wrinkling scores. This observation leads to the question whether the shape feature could be used in a two-layer hierarchical classifier where the shape is used to identify the genotype before the actual wrinkling score is provided by the

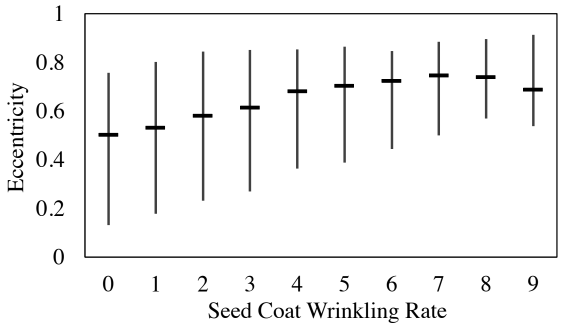


Fig. 9. Distribution of the eccentricity for the entire dataset for different seed-coat wrinkling levels

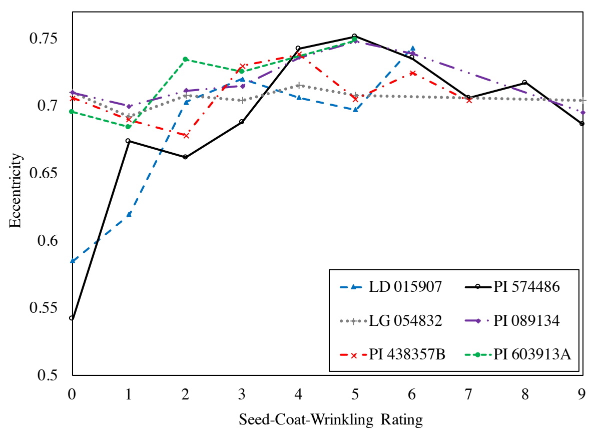


Fig. 10. Average eccentricity for seeds with different genotypes and coat-wrinkling scores

second layer of the classifier. This would allow the components of the second layer of the classifier to be trained as *experts* in each specific genotype, leading to a better overall performance of the wrinkling classification. In our future work, we will explore this possibility.

D. Multi-Class Relevance Vector Machine (mRVM)

Recently, various machine learning algorithms have been introduced and applied to seed assessment [21, 22, 26]. In this paper, we adopted multi-class Relevance Vector Machine (mRVM) [36] for seed coat wrinkling rating due to its ability to classify multiple classes (wrinkling scores ranging from 0 to 9) and to find good solution in the case of sparse representation of the data [37]. In order to train the mRVM, 60 percent (2049 individual seeds) of the seeds comprising the entire dataset were randomly set aside for training and the remaining samples (1366 individual seeds) were used for evaluation and testing. In order to compensate for bias in ground truth, the mRVM was trained using the median value of the rates provided by three experts. Also, a 5-fold cross validation on the training dataset employed. The best results were achieved by selecting Gaussian kernel with bandwidth of 0.1, and "top-down" approach – starting with the entire training data and progressively removing unnecessary samples – while keeping the total number of 35 vectors as the most relevant.

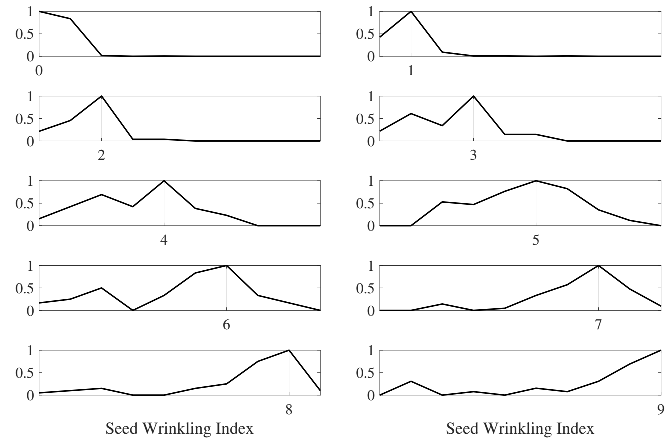


Fig. 11. Results for the mRVM-based classifier using a testing dataset of 1366 individual seeds. The Y-axes in each subplot represent the ratio between predicted scores and true positives, which is also the rows of the confusion matrix (Table II) in percentages.

TABLE II
A CONFUSION MATRIX FOR THE TESTING DATASET WITH 1366 INDIVIDUAL SEEDS

Class	0	1	2	3	4	5	6	7	8	9
0	189	158	3	0	1	0	0	0	0	0
1	121	284	26	2	2	0	2	0	0	0
2	17	36	79	3	3	0	0	0	0	0
3	9	25	14	41	6	6	0	0	0	0
4	4	11	18	11	26	10	6	0	0	0
5	0	0	9	8	13	17	14	6	2	0
6	2	3	6	0	4	10	12	4	2	0
7	0	0	3	0	1	7	12	21	10	2
8	1	2	3	0	0	3	5	15	20	2
9	0	4	0	1	0	2	1	4	9	13
Total accuracy within a tolerance of ± 1: 86.1%										

III. Results

After training, the classifier was tested using the hitherto unseen dataset (i.e. the remaining 40 percent of all rated seeds). However, in order to accommodate for the uncertainty in the ground truth provided by the experts (Figure 4), the system was tested for its ability to rate the seed-coat wrinkling within a tolerance of ± 1 of that rate. Figure 11 shows the performance of the classification on the testing dataset for each score given by the experts. It is important to notice that almost all seeds with zero wrinkling were actually rated as either zero or one – i.e. an almost perfect two-class classifier for *stressed* and *not-stressed* seeds.

The confusion matrix associated with the results above is represented in Table II. From this Table, we notice that the mRVM is able to classify 51.39% of the seeds exactly – i.e. zero tolerance – and 86.1% of the seeds within a tolerance of ± 1, which again corresponds to the uncertainty of the ground truth provided by the experts.

TABLE III
PERFORMANCE EVALUATION OF MRVM ON TESTING DATASET

Rates	0	1	2	3	4	5	6	7	8	9
Precision	0.55	0.54	0.49	0.62	0.46	0.31	0.23	0.42	0.47	0.76
Recall	0.54	0.65	0.57	0.41	0.30	0.25	0.28	0.38	0.39	0.38
Specificity	0.81	0.63	0.93	0.98	0.98	0.97	0.97	0.98	0.98	1

The Precision, Recall, and Specificity for the different classes (i.e. each of the seed-coat-wrinkling scores) are also shown in Table III. This table indicates that the mRVM achieved 0.76 and 0.55 precision for, respectively, the most (9) and the least (0) wrinkled seeds, while it classified the middle range much more poorly (an average 0.38 for rates 4 and 5). As already pointed out with respect to Figure 4, different experts mostly disagreed in their labels for the mid-range wrinkling rates. As such, the existence of greater uncertainty among experts should explain the decreased performance of our system, specially for mid-range rates. Moreover, the number of data points available for mid-range scores was relatively smaller than for the other classes – further explaining the decrease in performance.

IV. CONCLUSION

The proposed system for rating seed-coat wrinkling resulted in the development of a GUI for ground truth annotation, and a pipeline for seed segmentation, feature extraction, and classification using multi-class relevance vector machines (mRVM). Results for classification illustrated the ability of the mRVM to rate seeds within a range of ± 1 from the ground truth with an accuracy of 86.1% and an almost perfect accuracy for classifying stress vs. non-stress seeds. Uncertainty in ground truth data, in particular for the mid-range seed coat wrinkling scores, influenced the performance of the classification. Two new feature descriptors were introduced and evaluated for seed assessment. These feature were obtained using texture and shape levels in gray scale images. In the future, shape features will be used in a two-layer hierarchical classifier to improve overall performance of the wrinkling classification.

ACKNOWLEDGMENT

This material is based upon work supported by the National Science Foundation under Award Number IIA-1355406 and IIA-1430427.

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