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Identification of paddy varieties based on novel seed angle features

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ABSTRACT

The purpose of this article was to explore a new feature extraction method for classifying paddy seeds using a feature extraction algorithm to achieve the Horizontal–Vertical and Front–Rear angles. The method used fusion of angle features for classification, which were then compared to features such as seed color, shape, and texture. Experiments show that the proposed features work better in classifying paddy seeds in comparison with some of the standard features, and that the proposed features have an excellent discriminating property for seeds. The discriminating power of these features was assessed using the neural network architectures for the unique identification of seeds of four Paddy (Rice) grains: viz. Karjat-6(K6), Karjat-2(K2), Ratnagiri-4(R4) and Ratnagiri-24(R24). The classification accuracies of C olor–Shape–Texture obtained was 95.2% while the proposed method gave an accuracy of 97.6%.

1. Introduction

Crop productivity depends on the quality of the sown seed. From the cases filed by the victims (http://indiankanoon.org/doc/156016560/; http://indiankanoon.org/doc/157798498/; http://indiankanoon.org/doc/45758022/), it can be seen that the paddy crop was of different variety to the extent of 45:55 (http://indiankanoon.org/doc/156016560/). In another (http://indiankanoon.org/doc/157798498/) paddy crop was of mixture of three varieties and in one more the plants grew of different size and of different varieties, the seed was not of one quality (http://indiankanoon.org/doc/45758022/). This was the main motivating factor of this research. However, manually determining a pure seed from a seed lot is tedious, but it can be made simpler by automatically assessing seed images.

This paper proposes an algorithm to automatically identify and evaluate seeds. Feature extraction of seeds, like color, shape and texture are useful indicators when discriminating seeds. Because color is more or less consistent in seeds, using only color to discriminate is not practical (Chaugule and Mali, 2014). There is a need to identify more uniquely discriminating features. This paper discusses twelve such features (see Section 5.6).

2. Design issues

While extracting the features from images following design issues were found:

1. Various features that are needed for classification of various seeds and identifying the relevant seed features capable of reliably discriminating the seed of interest, is a challenging task.
2. Noise can reduce the reliability of the feature values measured. Therefore, finding robust features with respect to distortion, variations and deformation in environment and finding invariant features with respect to translation, rotation and scale are few more challenges.

3. Hypothesis

With the use of the calculation of angle as a feature, the accuracy of discriminating seeds will increase.

4. Literature survey

Pourreza et al. (2012) extracted 131 textural features, including 32 gray level textural features, 31 LBP features, and 31 LSP features, 15 LSN, 10 GLCM and 12 GLRM for each monochrome image of the bulk wheat samples. Mebatsion et al. (2012), Mebatsion et al. (2013) expressed Grain image boundary contours as chain-coded points and then approximated by 13 elliptic Fourier coefficients.

Huang (2012) calculated a pair of orthogonal eigenvectors of the covariance matrix. The color features—Rm, Gm, and Bm

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(i.e., the mean gray level of areca nut on the R, G, and B bands), the geometric features, the principle axis length (Lp), secondary axis (Ls), the centroid, axis number (Lp/Ls), area (A), perimeter (P), compactness ($4\pi A/P^2$) were computed using eigenvectors for areca nuts. Wiwart et al. (2012) presented a method to identify hybrids of spelt and wheat based on shape and color descriptors using principal component analysis. The color analysis was performed based on the average values of variables RGB for every ROI, which were then used to calculate the values of HSI and Lab, also Area, Perimeter, Circularity, Feret Diameter, Minimal Feret Diameter, Aspect Ratio, Roundness, and Solidity were determined.

Choudhary et al. (2008) extracted a total of 51 morphological features, 93 colour features, 56 textural features, and 135 wavelet features from each kernel. Delwiche et al. (2013) used size and shape features to determine whether a kernel is damaged; six features, including the 3-view mean solidity, minimum view minor-to-major axis ratio, minimum view contrast, mean entropy, maximum view entropy, and mean view homogeneity produce 91–93% accuracy. Al Ohali (2011) extracted features such as flabbiness, size, shape, intensity and defects.

In the previous work the accuracy achieved was 90.30–94.00% (Chaugule and Mali, in press). The accuracy needed to be increased to around 98% as per the standards prescribed by ISTA (Agarwal and Dadlani, 1986), so a need to identify more uniquely discriminating features was found.

5. Materials and methods

5.1. Block-diagram

The block diagram for the proposed system is as shown below in Figs. 1 and 2. Fig. 1 shows block diagram for classification using color–shape–texture (CST) features and Fig. 2 shows block diagram for classification using angle features.

The materials and methods used in the proposed solution are described below:

5.2. Material and grain samples

Digital camera – Sony 18.9 Megapixels and Images of the Paddy seeds wherein the seeds were supplied by the Seed Testing Laboratory-Pune, India.

5.3. Image capturing

There are no conventional datasets available, so we have created our own dataset. The images were acquired using above specified digital camera. The sample images for the specific type are

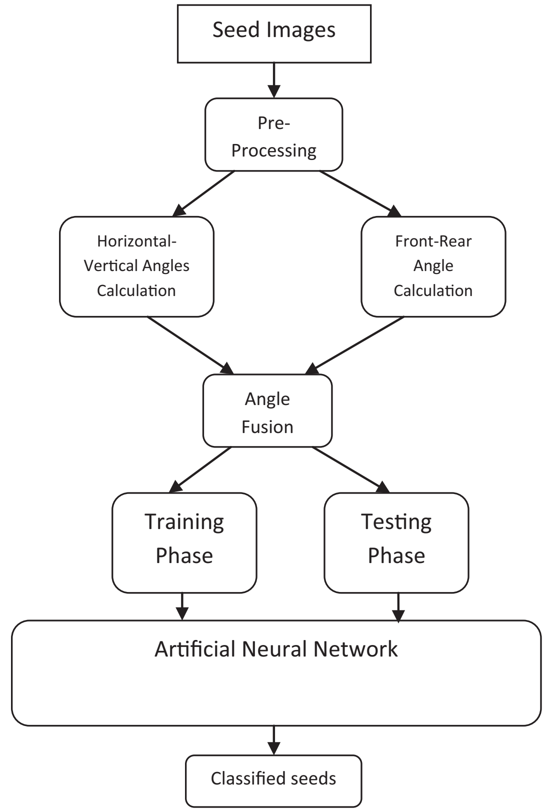

Fig. 2. Block diagram for classification using angle features.

shown in Table 1. The camera had 24 mm focal length. The camera was white balanced before the image acquiring session. Illumination plays a very important role in image acquisition. Manickavasagan et al. (2008) found that fluorescent tube lighting has the potential amongst the three illumination conditions; incandescent light, fluorescent ring light, fluorescent tube light (FTL) so FTL was used for this system. With the FTL: Model TL 40 W/TLD, 36W U_n: 240V, Philips, the images were captured at room light conditions without additional illumination. The saved images have the following parameters: 537 × 256 resolution, 350 dpi, 24-bit depth, JPG format. The numbers of images taken were one hundred and sixty four.

5.4. Image pre-processing

Image segmentation and morphological filtering was conducted in order to extract object features. In the pre-processing phase, any

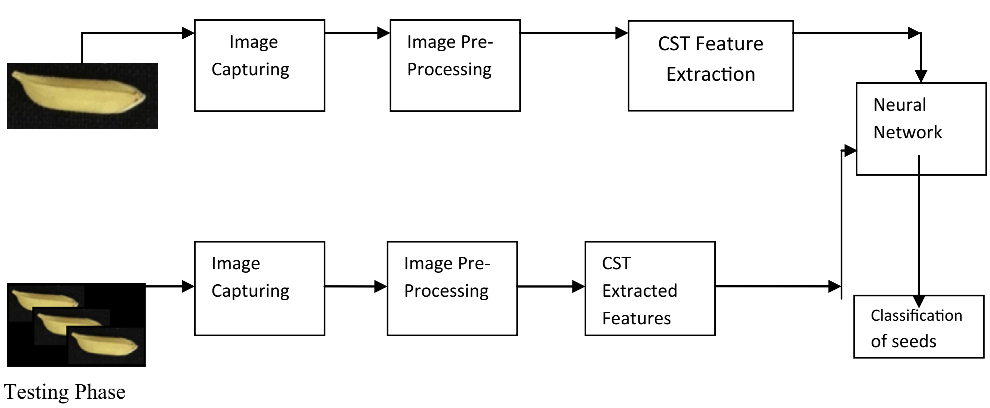

Fig. 1. Block diagram for classification using Color–Shape–Texture (CST) features.