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A texture feature extraction of crop field images using GLCM approach

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Abstract
To capture visual content of images for retrieval, feature extraction is one of the method. In this paper feature extraction is done using GLCM (Gray Level Co-occurrence Matrix). In this work 6 varieties of crop images are considered namely paddy, maize, cotton, groundnut, sugarcane and sunflower. There are many second order statistical texture features extracted using GLCM namely autocorrelation, entropy, cluster prominence etc. The four features namely autocorrelation, sum of squares of variance, sum of variance and sum of average are found to be predominant features for the present study. Considering texture as a feature, the average accuracy of 63.75% is obtained. The results show that these texture features are efficient and can be used for real time pattern recognition.

Keywords: Field images, GLCM, Features, Pattern recognition

Introduction

Image acquisition
The field image of paddy, cotton, maize, groundnut, sugarcane, sunflower are captured using sony digital camera .The images are captured with fixed focal length and under standard illumination.A total of 60 images of 6 varieties are considered for experimental study.
Some of the sample images are as shown in fig 1.

Fig.1. Images of paddy and maize

Preprocessing
The field images captured are basically 3500*4500 pixels. Certain preprocessing activities like resizing is done to all the 60 images and are resized to 512*512 pixels .The images are then filtered using median filter.

Feature extraction
From the study and literature survey, we found that feature extraction technique used are texture, color, shape and many more. In the proposed work feature extraction is done considering texture features.
Gray level Co-occurrence Matrix (GLCM)
Visual system of human beings use second order distribution of gray levels as discriminator in identifying textures. Some of the characteristics of texture are autocorrelation, cluster prominence, entropy, contrast and others. GLCM is very useful to obtain valuable information about the relative position of the neighboring pixels in an image. The co-occurrence matrix GLCM (i,j) counts the co-occurrence of pixels with gray value i and j at given distance d.The matrix element P(i,j) is separated from its neighborhood by a pixel distance $(\Delta x, \Delta y)$, one with intensity I and the other with intensity j. Number of gray levels is denoted by G. μ is the mean value of P.μ_x and$\mu_y$are the means and standard deviations of Px and Py. The direction of neighboring pixels to represents the distance can be selected, for example 135°, 90°, 45°, or 0°, as illustrated in Figure 2.

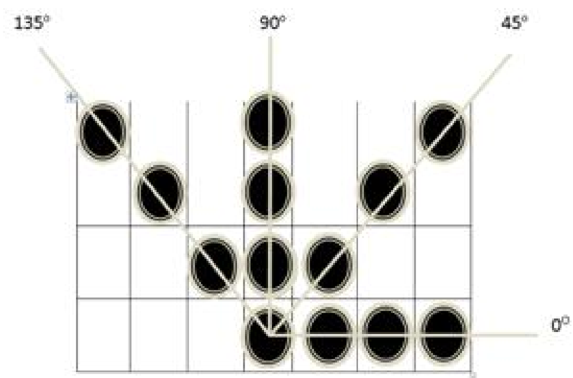

Fig 2 Directions in calculating GLCM

Results and discussion
All the 23 features were extracted and only 4 prominent features are considered for the present methodology. The four prominent features considered for the study are autocorrelation, sum of

squares of variance, sum of variance and sum of average. Repeating patterns like presence of periodic signal obscured by noise is called as autocorrelation and is given by equation (1).The autocorrelation values for the different varieties of field images are given in Table 1.Considering the tabular values the average accuracy of the extracted feature autocorrelation is as shown in the Fig.3.

Autocorrelation=$\sum_i \sum_j (ij).P(i,j)$ … (1)

Table1Autocorrelation feature values for different field images

Paddy	Cotton	Maize	Ground nut	Sugarcane	Sunflower
21.120	20.520	30.537	20.867	30.249	24.567
20.609	21.791	21.863	20.926	25.002	26.805
19.525	27.919	21.667	19.355	23.193	19.738
20.667	20.816	24.693	20.632	24.130	19.532
21.337	21.045	24.365	21.533	21.273	19.364
19.557	21.578	27.680	20.782	27.780	28.154
19.225	19.723	26.837	19.183	22.595	24.100
19.942	22.311	24.144	21.662	31.143	19.669
22.467	18.549	28.174	20.728	35.331	23.202
22.196	22.409	33.924	20.718	25.988	24.131

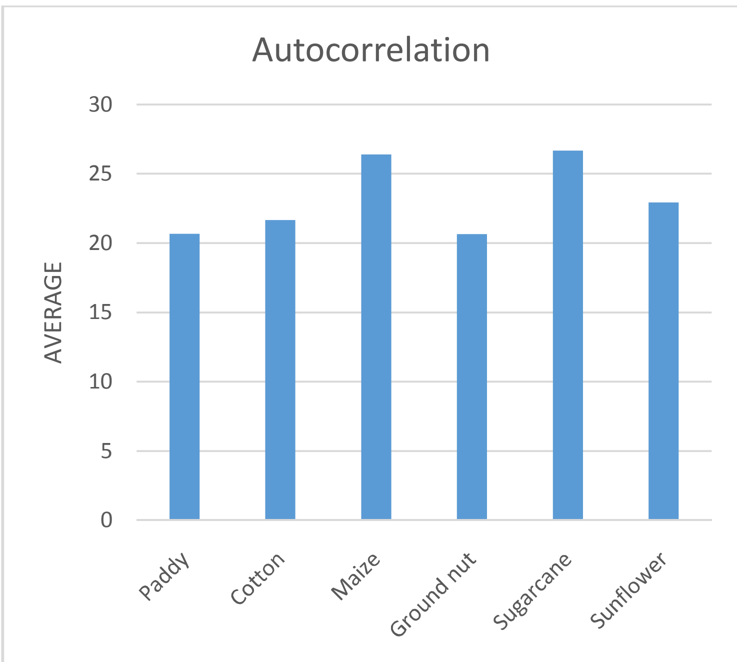

Fig 3. Average accuracy of feature autocorrelation

Sum of squares of variance is the sum of squared differences from the mean and is given by equation (2).

Sumofsquares of variance = $\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i-\mu)^2$ .P(i,j) … (2)

The values of the sum of squares of variances (sosvh) are given in Table 2.The classification accuracy for sum of squares of variance feature is as shown in the Fig4.

Table2Sum of squares of varience feature values for different field images

Paddy	Cotton	Maize	Ground nut	Sugarcane	Sunflower
21.137	20.479	30.458	20.999	30.207	24.666
20.625	21.812	21.854	20.967	25.000	26.827
19.584	27.925	21.671	19.363	23.173	19.835
20.709	20.734	24.671	20.556	24.134	19.476
21.352	20.962	24.316	21.489	21.272	19.318
19.626	21.544	27.674	20.726	27.782	28.097
19.186	19.672	26.808	19.173	22.551	24.040
19.933	22.330	24.085	21.581	31.103	19.541
22.422	18.565	28.146	20.957	35.238	23.222
22.201	22.349	33.876	20.864	26.016	24.155

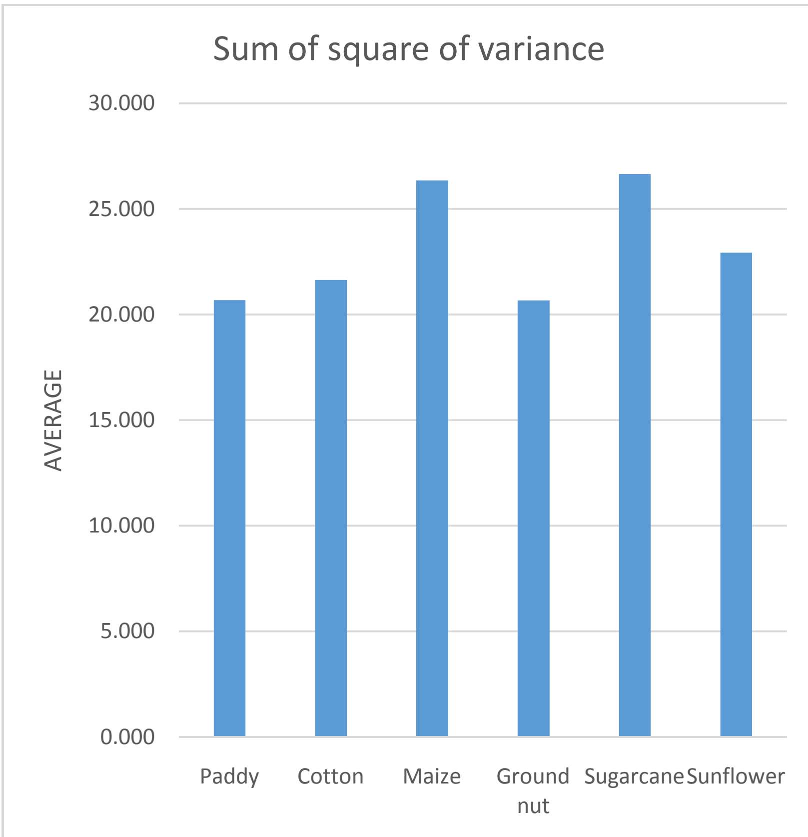

Fig 4. Average accuracy of feature Sum of square of varience

Variance is a measure of the dispersion of the values around the mean and combinations of reference and neighbor pixels. The extracted feature Sum of variance is given by equation (3).

$$\text{Sum of variance} = \sum_{i=1}^{2G} (1-\mu)^2 \cdot P(i,j) \quad \ldots \quad (3)$$

The values of sum of variance feature (svarh) are given in Table 3. The average accuracy for sum of variance feature is given in Fig.5.

Table3Sum of variance feature values for different field images

Paddy	Cotton	Maize	Ground nut	Sugarcane	Sunflower
58.323	53.867	81.093	50.693	83.802	60.889
61.892	54.082	53.009	52.001	62.850	69.783
54.422	73.626	51.702	47.587	58.965	46.566
60.652	58.171	61.246	54.608	63.615	49.667
57.045	59.902	61.263	56.352	55.613	51.426
49.007	56.876	70.834	57.599	73.063	74.230
56.719	52.150	69.489	49.079	59.591	65.691
58.066	58.409	60.971	59.609	86.125	63.018
69.075	45.837	73.646	49.175	103.646	62.278
66.596	60.526	96.592	51.408	66.145	62.072

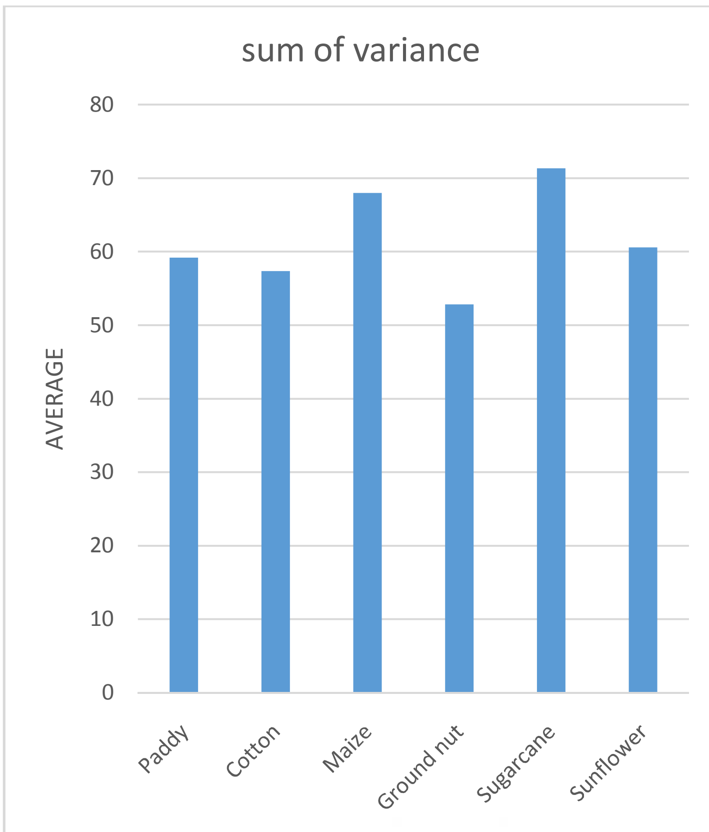

Fig 5. Average accuracy of feature Sum of average

Sum of average is the sum of all values and divided by the total number of values and is given by the equation (4).

$$\text{Sum of average (Mean)}=\sum_{k=2}^{2G} k \sum_{ij} P(i,j) \qquad \ldots\ (4)$$

The texture features extracted out of the above mentioned feature is given in Table 4. The average accuracy for the sum of average feature is given Fig.6.

Table4Sum of average feature values for different field images

Paddy	Cotton	Maize	Ground nut	Sugarcane	Sunflower
9.114	8.890	10.526	8.899	10.447	9.598
9.050	9.077	8.916	8.926	9.631	10.045
8.785	10.015	8.751	8.572	9.391	8.489
9.060	9.002	9.503	8.875	9.676	8.513
9.127	9.042	9.495	9.099	9.082	8.641
8.684	9.122	9.876	8.975	9.902	10.275
8.718	8.719	9.542	8.574	9.338	9.652
8.882	9.304	9.020	9.149	10.378	8.798
9.438	8.381	9.957	8.840	11.071	9.509
9.386	9.293	10.852	8.925	9.515	9.574

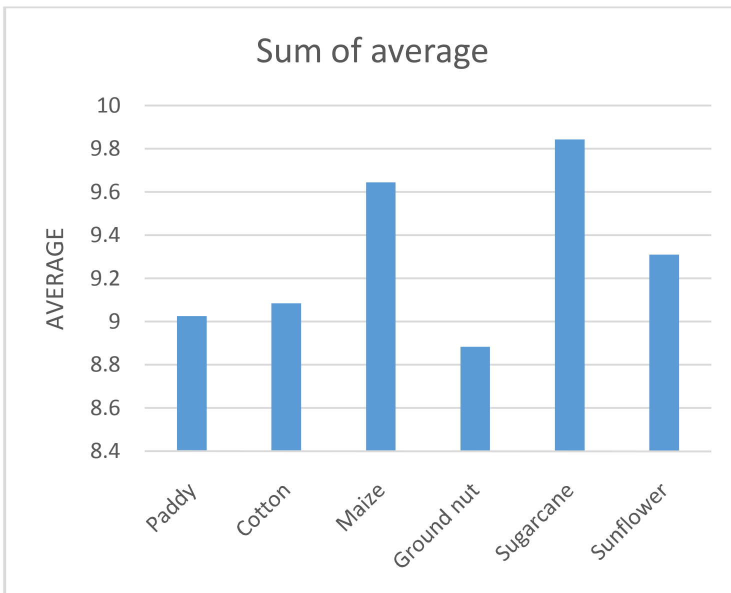

Fig 6. Average accuracy of Sum of average

Conclusion:

The work has reported an average accuracy of 63.75% with field images of 6 different types of crops. The texture features are deployed using GLCM algorithm. As an enhancement of the present work texture features can be combined with other features like color or vein and the average accuracy can be increased.This work finds its application in technology deployment in agriculture.

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