UAV Based Remote Sensing for Tassel Detection and Growth Stage Estimation of Maize Crop using F-RCNN

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1. Introduction

The information about the critical growth stage of maize such as tasseling is known very important because it indicates the transition from vegetative to reproductive growth, which will also help in taking potential actions to improve the crop health as well as optimizing the use of agronomic inputs. Manual observation of different stages of the crop is a difficult and challenging task as the height and density of the crop increases day by day. To reduce human efforts, researchers have used computer vision approach to detect and count the number of tassels in the images captured from the static camera. To reduce human efforts, computer vision based approaches are proposed wherein [1]-[2], color, shape, and texture based features used while in [3], convolutional neural network (CNN) based approach used for tassel detection and counting in images from a static camera. However, these works also do not cover the complete growth of tassel at different stages as it changes its color and texture as it grows. It is a difficult problem to detect and count tassel at every stage. In this paper, a framework is proposed to detect and count tassel at different stages using UAV as it is hard to collect data from a static camera in large fields. UAVs have the potential to provide a feasible solution for the large scale and high throughput phenotyping. The processing techniques of static images will be incompatible for images acquired via UAV due to the difference in spatial resolution, variation in background and moment of UAV. To the best of our knowledge, this is the first study on the detection of tassels and estimation of tasseling stages of maize crop using UAV based remote sensing.

2. Proposed Method

To address this issue, we have proposed a CNN based framework to detect the growth of tassels and estimate heading (start of emergance of tassel at least in one plant), days to 50% tasseling (DFPT)- the day when 50% plants have at least one tassel, stages of the maize crop. Faster RCNN (F-RCNN), [4], which is trained on ImageNet dataset, is fine tuned for our dataset. F-RCNN consistes of two modules: Region proposal network that proposes object regions and object detector which classifies objects and creates bounding box around them. The performance of F-RCNN is compared with YOLO (You Only Look Once) [5], which is pretrained on COCO dataset.

For this study, the dataset is acquired by flying UAV periodically at a height of $10m$ from maize field with an area of $10m \times 10m$ at Professor Jayashankar Telangana State Agriculture University (PJTSAU), Hyderabad, India. The primary challenge in UAV based remote sensing is acquiring appropriate plot image for processing from original UAV images. AgiSoft Photoscan Software is used to create orthomosaic from this data which is further segmented to get appropriate images of plots which are used to develop training and testing datasets. The number of plants in each plot is recorded, as half of this number will be an indication for DFPT stage of a plot.

3. Results and Discussion

To train F-RCNN and YOLO models, 250 images in which each image contains approximately 25 tassels are used. Manual observations for heading stage and DFPT

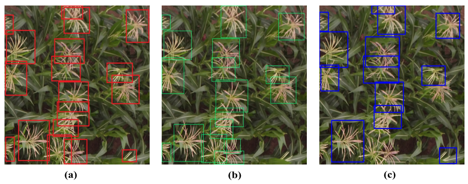

Figure 1. (a). Labelled Original Image (b). Detection by F-RCNN (c). Detection by YOLO

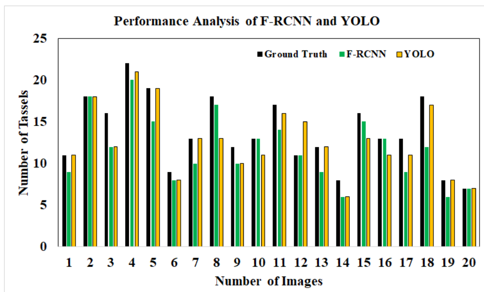

Figure 2. Tassel Detection of F-RCNN and YOLO on Test Images

stage are used as ground truths and F1 score [6] is considered as a performance metric for evaluating model performance. F-RCNN and YOLO have been evaluated for detecting tassel in the images. The 20 images are used to test the performance of models. Fig.1, shows the detection performance of F-RCNN and YOLO. In Fig. 2, tassels count by F-RCNN and YOLO are compared with ground truth. It can be observed that YOLO give count close to ground truth but YOLO has low precision accuracy compared to F-RCNN as YOLO misclassify more. From Table 1, it can be observed that F-RCNN model performs better and recognizes the tassel with $F1$ score of 0.909 compared to YOLO model which has $F1$ score of 0.878. Therefore, F-RCNN model used to count the tassel in images of plots and estimate dates for heading and DFPT stages of maize crop.

The comparison of manually observed dates and estimated dates by proposed framework for heading and DFPT stages of the maize crop is shown in Table 2. In Table 2, O_{HS} and O_{DFPTS} indicate the manual observation for heading(start of emergance of tassel) and the day to 50% tasseling stages where E_{HS} and E_{DFPTS} represent the dates estimated by proposed framework. Due to limited space, the observations of only nine plots have been included in the table. From Table 2, it can be observed that the model can provide accurate information about crop growth stages. Due to lack of data, it was difficult to pin the exact date for stages. The estimation of dates for different stages have been given in Table 2 based on rate of change in count of tassels. The data should be collected daily during vegetative to reproductive growth stage to predict exact date.

Table 1. Performance Analysis of F-RCNN and YOLO for Detecting Tassels

Images	F1 Score_RCNN	F1 Score_YOLO
1	0.909090909	0.909090909
2	1	1
3	0.857142857	0.857142857
4	0.952331063	0.837209302
5	0.882306919	0.842105263
6	0.823485811	0.823529412
7	0.869565217	0.846153846
8	0.914285714	0.838709677
9	0.909090909	0.727272727
10	1	0.916666667
11	0.903225806	0.909090909
12	1	0.846153846
13	0.857142857	0.833333333
14	0.857142857	0.857142857
15	0.967741935	0.827586207
16	1	0.916666667
17	0.818181818	0.916666667
18	0.8	0.857142857
19	0.857142857	1
20	1	1
F1 Score	**0.908893877**	**0.8780832**

Table 2. Performance Analysis of F-RCNN for Estimating Growth Stages

Plots	O_{HS}	E_{HS}	O_{DFPTS}	E_{DFPTS}
1	15 Dec	Before or on 17 Dec	22 Dec	20 Dec
2	17 Dec	Before or on 17 Dec	23 Dec	20 Dec+ 1 or 2 days
3	17 Dec	Before 17 Dec	27 Dec	20 Dec+ 2-3 days
4	17 Dec	Before 17 Dec	24 Dec	20 Dec+ 1 or 2 days
5	15 Dec	Before or on 17 Dec	21 Dec	20Dec
6	15 Dec	Before 17 Dec	22 Dec	20 Dec
7	15 Dec	Before 17 Dec	21 Dec	20 Dec
8	15 Dec	Before or on 17 Dec	21 Dec	20 Dec
9	15 Dec	Before 17 Dec	29 Dec	20 Dec+ 1 or 2 days

4. Conclusion

In this study, we have proposed a UAV based remote sensing framework to monitor and estimate growth of tassel which gives information about different growth stages-heading(start of emergence of tassel), DFPT of the maize crop. A CNN based F-RCNN and YOLO models are evaluated for tassel detection from it's emergence to reproduction stage. F-RCNN with F1 score 0.909 provides better detection compared to YOLO which has F1 score of 0.878. Hence, F-RCNN has been used to estimate the heading and DFPT stages of maize crop. From the performance analysis it can be concluded that a UAV based remote sensing framework using F-RCNN can be an alternative way for manual observation of different growth stages of maize crop.

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