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Straw Row Position And Orientation Reconstruction Through Image Segmentation

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Abstract

This paper investigates a new approach in straw row position and orientation reconstruction in an open field, based on image segmentation with Fully Convolutional Networks (FCN). The model architecture consists of an encoder (for feature extraction) and decoder (produces segmentation map from encoded features) modules and similar to [1] except for two fully connected layers. The heatmaps produced by the FCN are used to determine orientations and spatial arrangments of the straw rows relatively to harvester via transforming the bird's eye view and Fast Hough Transform (FHT). This leads to real-time harvester trajectory optimization over treated area of the field by correction conditions calculation through the row's directions family.

Keywords: grain harvester, semantic segmentation, convolutional neural networks,

INTRODUCTION

In recent years information technologies development lead to a significant increase in R&D projects in the area of self-driving vehicles and robotic systems: advanced driver assistance systems (ADAS), self-driving cars, manufacturing robots [2], etc. No wonder, that major part of these projects is dedicated to the agricultural area: with a predicted world population increase up to 10 billion by the 2050 year, it is obvious, that population problem can't be solved without corresponding increases of agricultural effeciency and automatization. During the last 20 years, these studies made a significant progress: in 90's of XX-century, Japan, USA and Europe first introduced the usage of GPS-integrated agricultural vehicles within the "Precision Agriculture" concept. Now the complexity and accuracy of such solutions has significantly increased because of various types of new sensors, such as optical encoders, LIDAR/LEDDAR, as well as mathematical algorithms and steering controller systems, etc. All these technologies are already implemented in manufacturing solutions in various fields of agriculture: spraying [3], soil preparation and seedling [4], rootstock planting [5], harvesting [6] etc.

RELATED WORKS

Nowadays in the field of Precision Agriculture and Livestock Farming many types of sensors are used in the autonomous and semi autonomous driving [7-9] to solve cut-edge detection [10-12] and row detection [13-15] tasks. Machine vision-based systems mimic the operator's perceptive process [13]. Images can be acquired without depth information with monochrome (near infra-red) or color cameras and stereo vision technology [16-18] and are widely used to restore depth information. RGB-D and flash light detection (ToF) cameras give direct 3D vision information and points clouds that are captured from laser (LADAR) or light detection and ranging (LIDAR) devices [8, 9, 19].

In vision-based systems camera location and algorithm development are related. For example, the algorithms discussed in [11]were used with a camera mounted directly on the head of the combine harvester. In spite of a more complicated scene geometry vehicle cabin mounted camera systems [15, 16, 20] are more universal with respect to different types of tasks and have become a de-facto standard .

Monocular vision-based crop rows detectors generally separate plants images from soil, and then find rows by fitting straight lines to the resulting binary image. Authors [14, 21] use near-infrared spectrum monochrome cameras and image binarization (intensity segmentation). More sophisticated color-based crop row detectors use color segmentation focused on the separation of green plants (crops and weeds) from the rest. Many "vegetation indices" ([22-24] etc.), complementary techniques like fuzzy clustering [25, 26] and binarization method selection are used to become more robust to illumination changes and shadows. Color segmentation approach is ineffective when segmented objects are no longer green and using color-based only method becomes difficult.

Crop rows have regular structure and several approaches avoid the segmentation step by instead searching for periodic variations in image intensity ([21, 27-29], etc.) under the assumption that the crop rows lay at the peaks in these periodic variations.

Crop rows direction and position are estimated by fitting lines to the row fragments (segments) with standard image analysis technics such as: fixed template matching [30]; linear regression [14, 28]; the Hough transform [22, 31, 32]; random sample consensus [16]. Due to perspective distortion parallel rows became non-parallel on images and vanishing point detection technics can be used. Another popular approach is bird's eye view [12, 31].

Due to the complexity of the image segmentation task under controlled conditions recent works [15, 33, 59] try to combine intensity, color and texture information to obtain more robust algorithms.

Over the past several years Convolutional Neural Networks [34] have shown remarkable results in computer vision and related tasks, such as image classification [35-37], object detection [38-40], transfer learning [41, 42]. Recent works have also shown that CNNs can equally well apply to pixel-level labelling tasks, such as semantic segmentation [1, 43].

Most earlier works on semantic segmentation rely on a pre-segmentation into superpixels or other segment candidates, and extract features and categories from individual segments and from various combinations of neighboring segments [44-50]. Then an inference procedure based on a graphical model finds the most consistent set of segments which covers the image.

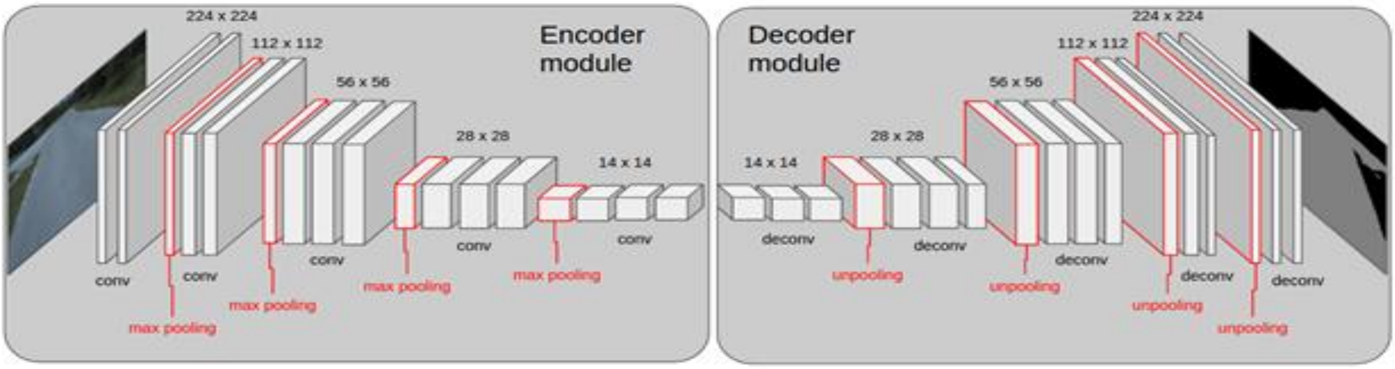

Figure 1: The model architecture

There is a number of problems with the approach described above. First of all, final semantic segmentation results heavily depend on heuristic segment proposal algorithm. Secondly, it is not clear how to integrate large available context from the whole image into decision making procedure about the region being classified. And, at last, pre-segmentation approaches are very computationally expensive and can not be applied in real time settings.

Another line of works uses convolutional networks in a patch based fashion [51, 52] where the model classifies the central pixel of an image crop which is relatively small compared to the whole image. The segmentation map is obtained by cropping an image and making a class prediction at every possible location. Although the properties of convolutional network architecture allow to calculate the segmentation map efficiently [52], the problem of integrating global features from the whole image (the problem of small receptive field) into decision making still remains.

The most successful recent results for semantic image segmentation are based on Fully Convolutional Networks (FCN) and their modifications [1, 43, 53, 54]. FCN-based models take the image as an input and produce another image as an output which usually is interpreted as segmentation map. In this formulation, one can construct FCN-based models with arbitrary large receptive fields making use of global contextual information from an entire image. Natural end to end training abilities, fast and straightforward inference procedure are another key properties of FCN models.

The direct prediction with FCN-based models usually results in low-resolution segmentation map. To address this problem, a number of recent methods focus on refining the low-resolution prediction to obtain high resolution segmentation map. The following works [53, 54] use graphical models on top of FCN, [1] introduces a promising approach of using learnable deconvolutional layers to upsample the low-resolution predictions. In this work we chose to adopt the deconvolutional network architecture from [1] for the task of straw row position and orientation reconstruction through image segmentation.

NETWORK ARCHITECTURE

The model architecture consists of encoder and decoder modules as shown in Fig. 1. Generally speaking, the encoder module is responsible for feature extraction, whereas decoder module generates segmentation map given the encoder features. The encoder and decoder modules have symmetrical configuration in a sense that for every convolutional layer in encoder there is a deconvolutional layer in decoder and each pooling layer in encoders corresponds to a specific unpooling layer in decoder. Our architecture is similar to the one described in [1], except that we have removed two fully connected layers.

DATASET

The dataset consists of images that were obtained from a camera mounted on a performing agricultural work harvester as schematically depicted in Fig. 2. The images were manually annotated to form the Ground Truth segmentation maps. The segmentation maps include following classes of objects:

- Background: none of the following
- Straw Row
- Harvested Crop
- Uncut Crop
- Combine Head

All training segmentation maps were made mannualy. All in all there are 925 marked up images in Full HD image format. Segments are represented by a set of simple polygons.

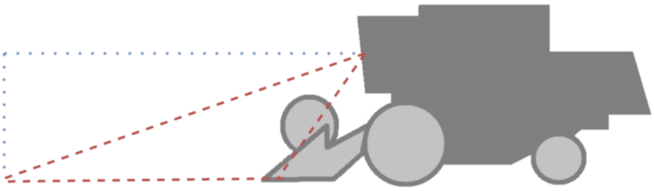

Figure 2: Harvester camera installation point and view angle

	Background	Straw Row	Harvested Crop	Uncut Crop	Combine Head
Percent of pixels	27%	5%	17%	41%	10%

Figure 3: Percent of pixels per each class among all pixels in the available images

According to common practice, 60 percent of randomly chosen images were assigned to training set, 20 percent were assigned to validation set and 20 percent were assigned to test set.

AUGMENTATION OF TRAINING DATA

Since there were only 925 maked up images in our training set we had to use data augmentation techniques in order to get an appropriate training set size. To augment training data following transformation were applied to original training images:

- Horizontal flips
- 4-9 degree clockwise or counterclockwise rotations
- Random 80% crops
- Color transformations: minor changes in each color channel

After augmenting training images with the transformations described above, 22200 images were obtained, since applying the transformations to a single image allows to obtain 24 augmented images.

OPTIMIZATION

Transfer learning techniques were applied to initialize the weights in the encoder module. In particular, the weight values of VGG 16-layer net pre-trained on ILSVRC [55] dataset were used. The weights of decoder module were initialized with zero-mean Gaussians.

The proposed network implementation was based on Caffe [56] framework. The standard stochastic gradient descent with momentum was used for optimization. The learning rate and momentum had the values of 0.01 and 0.9 respectively. During the training process the learning rate value was constant. L2 regularization with weight decay value of 0.0005 was used. The minibatch size was set to 64. The network converged after 16 epochs or 44400 iterations.The best model in term of validation per pixel accuracy was trained for 85 hours on a single Nvidia GTX Titan X (Maxwell) GPU with 12GB memory.

RESULTS EVALUATION

Two models were trained: with and without data augmentations. Let's denote these models as *deconv+* and *deconv* respectively. The quantitative results of the models are presented in Table 4.

	Background		Uncut Crop		Straw Row		Combine Head		Harvested Crop		Global	
	Acc	IoU	Acc	IoU	Acc	IoU	Acc	IoU	Acc	IoU	Acc	IoU mean
deconv	0.987	0.969	0.956	0.914	0.747	0.672	0.996	0.978	0.885	0.765	0.936	0.859
deconv+	0.991	0.984	0.964	0.944	0.849	0.768	0.995	0.980	0.932	0.842	0.958	0.904

Table 4: Per class evaluation metrics on the test set

From Table 4 we can see that training data augmentation was helpful in a sense that the corresponding model works better in terms of intersection over union (IoU) and per pixel accuracy (Acc).

The model that makes use of data augmentation correctly classifies 95.8 percent of all pixels on the test set. Besides, for the well represented classes such as background, the accuracy is extremely high. On the other hand, the accuracy for underrepresented class of straw row is below 85 percent.

STRAW ROW GEOMETRY RECONSTRUCTION

The goal of active rear-wheel steering is to keep straw row between forward wheels of the harvester during moving over treated area. Trajectory above the middle line of straw row additionally preserve harvester from dangereous situations, since straw rows are automatically formed in a such way that it is guaranteed that harvester will meet no stationary obstacles on its way when moving along straw rows.

After receiving heatmap from CNN depicted on Fig. 5 it is possible to solve task of straw rows geometry reconstruction, i.e. to find the direction and the offset of the straw row relative to harvester reference frame. Orientation and spatial arrangement of the rows relatively to harvester are required to generate corrective action in a steering subsystem of a harvester.

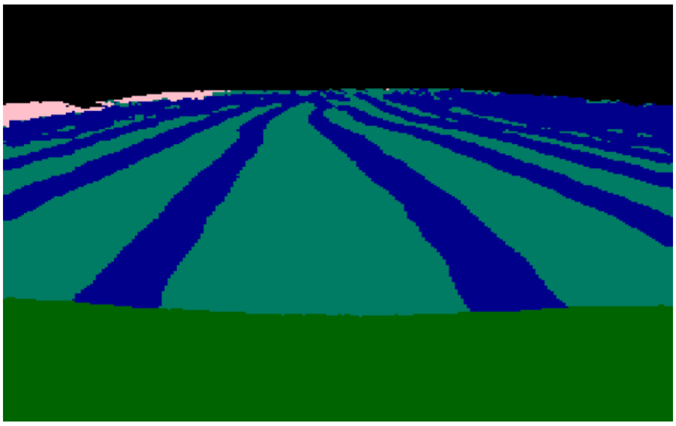

Figure 5: Heatmap produced by CNN

The straw row class is the only one to be allocated from the initial heatmap for following processing stage. Other classes, including combine harvester head, uncut crop, harvested crop and background were disregarded in this case. The initial heatmap contains redundant information. Disregarded classes can be further used in other tasks of automatical steering. For example automatical steering with reference to edge between uncut and harvested crop, crop rows and etc.

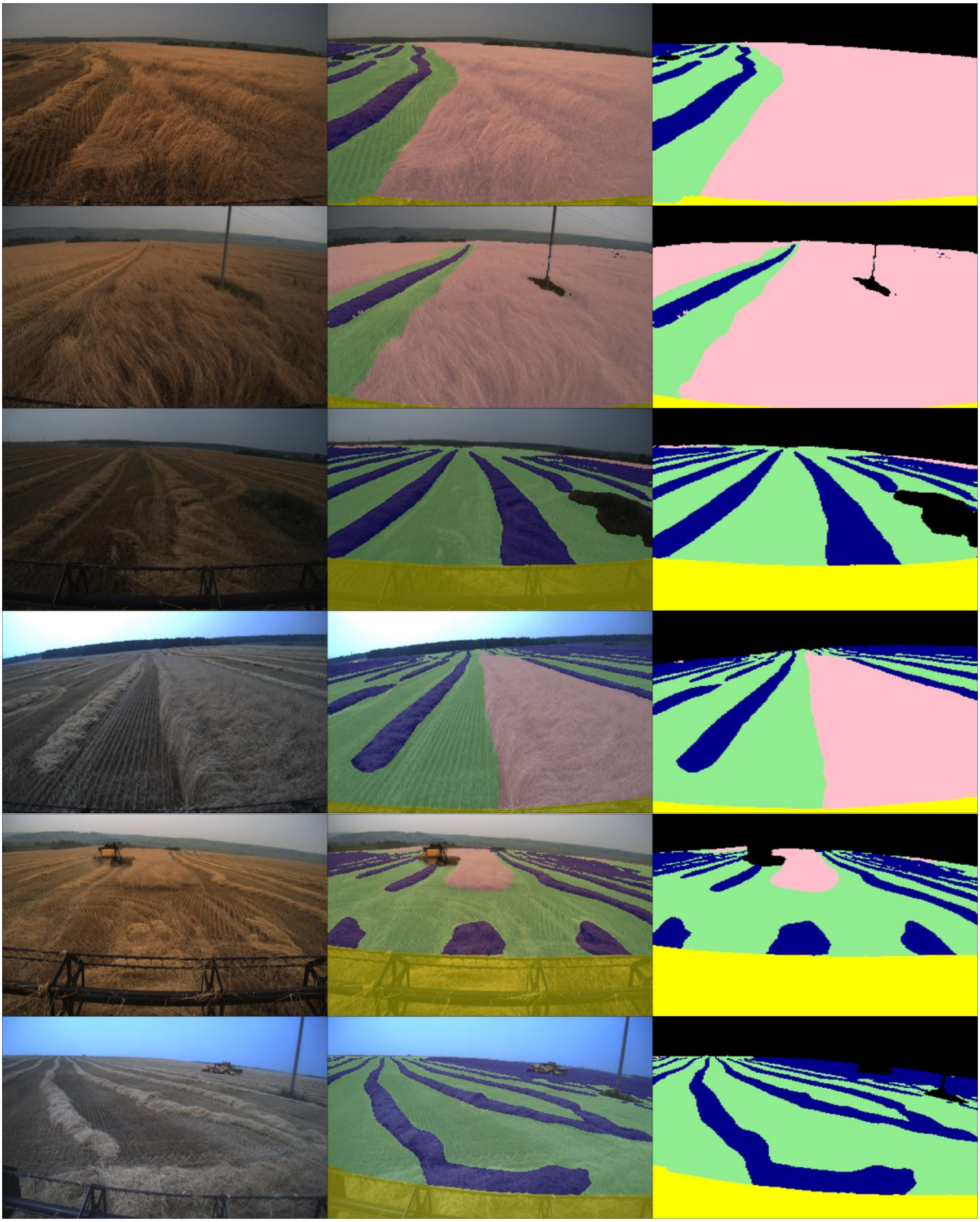

Figure 6: Segmentation examples produced by our model. Original image (left column), predicted segmentation (right column), segmentation shown on top of the original image (middle column)

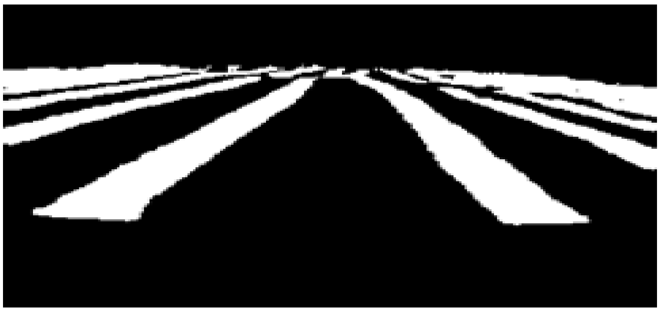

Figure 7: The straw row class heatmap visualization

On Fig. 7 mask for straw row segments is depicted. The bird's eye view transform applied to that mask. The bird's-eye view is perspective transformation technique which generates a top

Figure 8: Bird's-eye view transform

view perspective of an image. Parallel stractures on the ground become truly parallel. To perform the bird's-eye perspective warping accurate camera calibration technique is essencial. As result of bird's-eye view transformation straw rows transformed into segments with persistent form and similar orientation as depicted on Fig. 8.

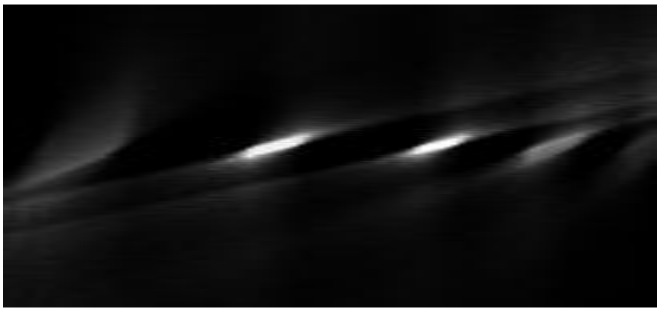

Figure 9: Fast Hough transformation of bird's eye view image (FHT1)

To detect the relative directions and offsest of the rows on the bird's-eye image the Fast Hough Transform (FHT) [57] is applied. After normalization to the range [0, 255] there are several bright blobs appiared as depicted on Fig. 9. Each blob corresponds to a separate straw row on the bird's-eye image.
In purpose of direction measurement noise reduction the additional FHT is applied to the result of first FHT. FHT of order 2 (FHT2) sharpens the maximum essentially as depicted on Fig. 10. The physical meaning of the FHT2 is that it detects the mean direction of all observable straw row segments.
Number of bright lobs on Fig. 9 represents the amount of

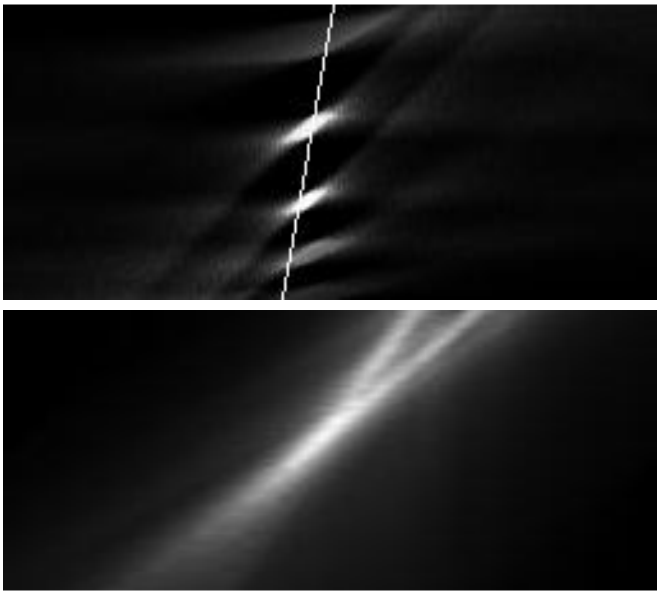

Figure 10: Fast Hough transformation of FHT1(FHT2)

straw rows. To find the best directions for each row independently it is required to perform the FHT for each row independently and choose the local direction with minimal deviation from global direction of all straw rows.

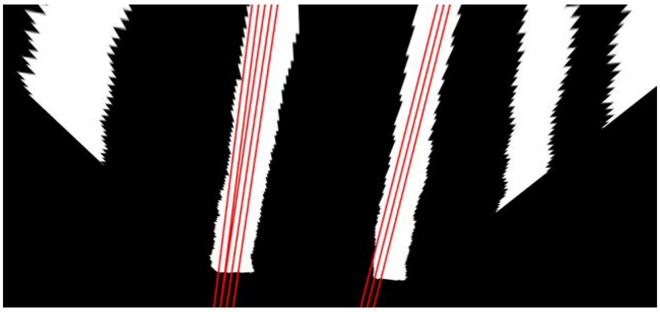

Figure 11: The best directions for each straw row

The last stage is to select the unique line with optimum cretera – select the closest straw row. On previous stage there was the family of directions. For the best choice of unique direction line denote cost function as a perpendicular distance from the center of harvester head and to a line (direction) in Euclidean metrics.

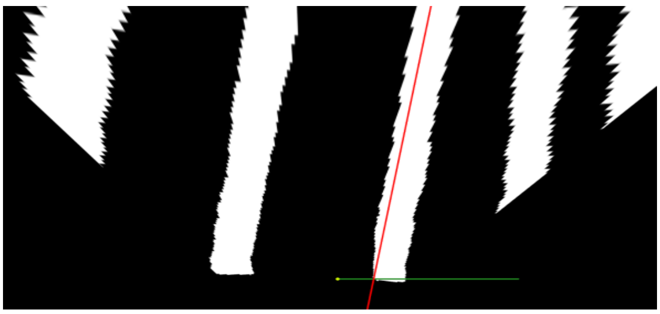

Figure 12: The best direction (red line), harvester head (green line)

The resulting line corresponds to the middle line of the closest segment. The resulting line can be further processed with some control subsystem to generate steering commands to follow the straw row.

EXPERIMENTAL RESULTS

The proposed CNN was tested on the Advantech UNO UNO-3083G-D64E embedded computer. Brief computer configuration is given below in Table 13.

Processor	Core i7-3555LE
GPU memory	4gb
GPU card	PNY Quadro k1200 4GB PCIE 4xmDP DVI 1046/1253 128-bit DDR5 512 Cores 4xmDP to DVI-D adapter
Operational System	Ubuntu 16.04 LTS

Table 13: Hardware details

Processing time of each frame was 165 ms: processing frame by CNN – 150 ms, computing straw row position, orientation – 15 ms. This processing time resulted in a final performance of 6 frames per second. For this purpose of the harvester real-time automatical steering processing frequency of 6 FPS is sufficient.

CONCLUSION

This work demonstrates that the adopted deconvolution network architecture is suitable for straw row segmentation. A series of experiments was conducted to validate high quality segmentation.

Proposed neural network architecture is efficient both in terms of memory and computing time. The network is trained end-to-end since the proposed approach yields accurate straw row segmentation in roughly 6 frames per second.

Accurate camera calibration and Bird's-eye view transform is essencial for straw row geometry reconstruction.

The straw row geometry reconstruction can be done with sufficient processing speed to meet the requirments of the harvester automatic steering along the rows.

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