Tillage Boundary Detection Using Heat Map Regression for Autonomous Tractor

DongHee Choi
Department of Computer Engineering, Wonkwang University, Iksan 54538, Korea.
heh0177@naver.com

KangHan Oh
Department of Computer Engineering, Wonkwang University, Iksan 54538, Korea.
khoh888@wku.ac.kr

ABSTRACT

This paper proposes the tillage boundary detection method using heatmap regression for an autonomous tractor. Recently, CNN-based tillage boundary detection approaches have been proposed, and a significant success exists. However, their mechanisms rely heavily on heuristic and complex post-processing to detect the final self-driving direction from CNN's output. Moreover, since the tillage environment contains various noises factors such as weather, time, and ground textures, it is very challenging task. To tackle this issue, we present the heatmap regression-based approach to detect the tillage boundary. In our work, we directly detect the heatmap points on the tillage boundary using U-Net. In the experiments, we constructed the tillage boundary dataset, and our method has achieved outstanding performance without the complex post-processing.

KEYWORDS

Autonomous traveling, agricultural machinery, boundary detection, CNN

1 INTRODUCTION

Recently, a smart agriculture has been an important study due aging society and shrinking workforce. In particular, an agriculture tractor, which is widely utilized for various agricultural automation tasks, is essential tool. For this reason, a self-driving tractor has been a significant study for researchers, and various computer vision and global positioning system (GPS)-based methods [1, 2] have been proposed. Recent years, Deep learning-based methods have been proposed and significant progress exists. Deep learning-based approaches are being used widely to yield the remarkable performance in various agricultural automation tasks [3-11]. Especially, Convolutional Neural Networks (CNN), which is specialized architecture for analyzing images, are famous for detecting the tillage boundary lines [12,13]. CNN is widely utilized for image classification [3], object detection, and segmentation. For the tillage boundary detection studies, the existing methods [12, 13] employed the sliding window technique to extract the local pattern of the tillage boundary. A classification task was conducted to detect the tillage boundary lines. However, this approach suffers from local noises because this cannot extract the global context features, which is essential to find the tillage boundary from the region proposal patches. In addition, complex and heuristic post-processing methods are required to define the final tillage boundary and driving direction of tractor. In this study, we proposed Fully Convolutional Network (FCN) based method to detect the tillage boundary lines. In the method, we employed heatmap-regression method to detect the tillage boundary points, and each point is future used to find tillage boundary. This way, complex post-processing is not required since the simple non-maximum suppression method defines the boundary points effortlessly. Moreover, unlike the region proposal-based approach that requires multiple operations, it only requires single feed-forward computation, thereby leading to better time efficiency. In the experiments, our method is evaluated on a custom tillage boundary dataset and shows the robustness with the local noise and better performance.

2 PROPOSED METHOD

2.1 Dataset collection environment

When conducting the tillage work, its features can be divided into pre-tilled, post-tilled, and background regions, as shown in Fig 1. In the pre-tilled region, we can see that various noises factors such as crops and weeds. On the other hand, smoothed ground features

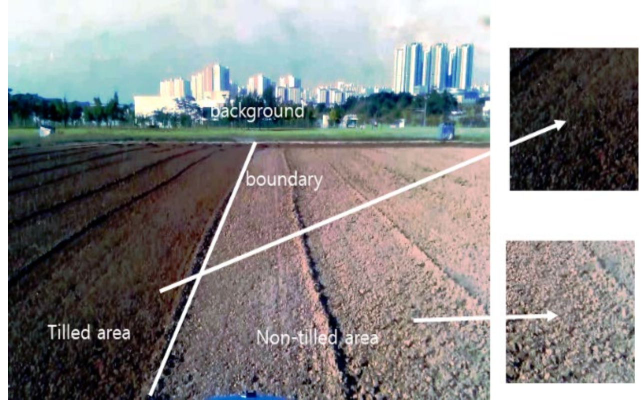

Fig. 1. Image obtained by RGB camera

Fig. 2. RGB camera mounted on the front side of a tractor

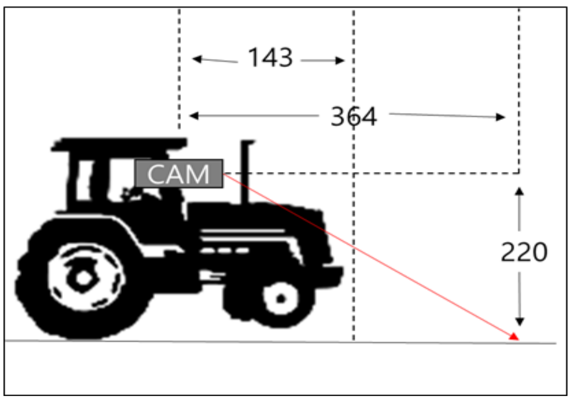

Fig. 3. Camera installation environment (unit: cm)

were observed in the post-tilled area. We can easily see that the discriminative features (shape, contrast, color, and texture) between pre-tilled and post-tilled areas. Then our primary goal is to detect the boundary between them for self-driving direction.

To acquire the tillage boundary dataset, we used LS-Mtron XU6168 (Fig. 2 left) as a tractor model and the action camera (Hero7, GoPro – Fig. 2 right) mounted on the tractor's front top center. Note that, as shown in Fig. 3, we adjusted the camera position that includes front part of the tractor so that CNN learns tractor's position.

2.2 Heatmap regression for the tillage boundary detection

In this study, we employed U-Net architecture consisting of only convolutional layers and Fig. 4 shows the architecture. We followed the standard U-Net architecture [14]. The U-Net consists of encoder, decoder, and skip connections. Each layer contains two convolutions, each followed by leaky Rectified Linear Units (ReLU). decoder. Fig. 5 illustrates the proposed framework including the non-maximum suppression for detecting the final tillage boundary points. As mentioned previously, our network directly regresses the tillage boundary points and we can simply extract the boundary points by the non-maximum suppression as

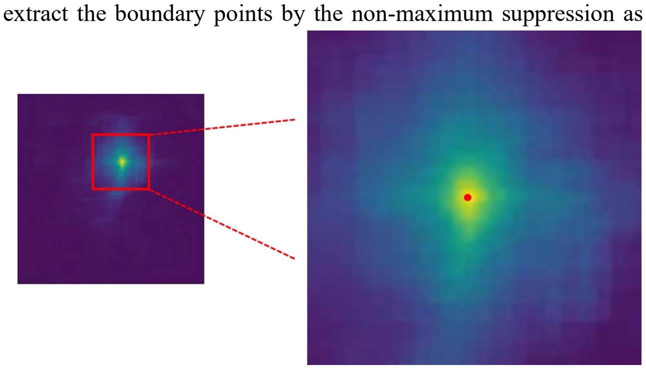

Fig. 5. Non−maximum suppression method for detecting the centroid of heatmap

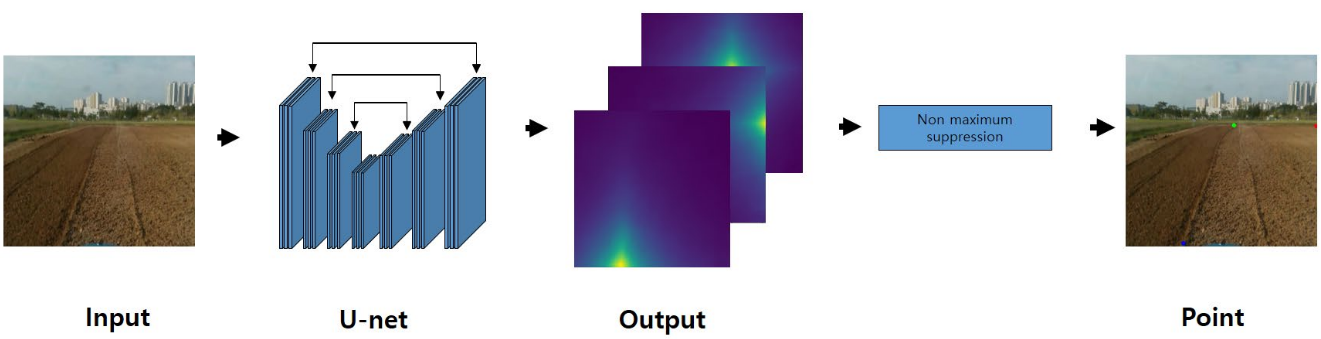

Fig. 4. The U−Net Architecture

shown in Fig. 5. Through the experiments, the number of filters for the encoder {64,128,256,512} and decoder {512,256,128,64} are used.

Table 1. Performance of the proposed method according to heatmap scales

Heatmap scale level	Euclidean distance			
	Average	Point 1	Point 2	Point 3
1	12.96	10.63	5.50	22.75
2	12.21	8.65	5.61	22.37
3	11.19	8.89	5.24	19.45
4	11.94	11.11	4.62	20.11
5	**10.55**	**8.55**	**5.34**	**17.76**
6	10.84	7.75	5.09	19.67
7	12.76	8.97	5.04	24.27
8	14.93	9.86	5.94	29.00

For 700 epochs, U-Net is trained from scratch using L2 loss function and Adam optimizer with a mini-batch size of 1 and an initial learning rate of 1e-5. When learning heatmap regression networks, the data augmentation consisting of random rotation [-10, 10], left-right flip, and intensity changes (brightness, contrast, and hue) is implemented and the cosine annealing method is employed to decay learning rate.

3 EXPREMENTAL RESULTS

In this section, we present experimental results and the implementation environment. The proposed method is implemented with the Pytorch framework and Python. We conducted the experiments on an Intel Core i9-10980XE with a 3.50 CPU, 128 GB of memory, and an RTX 3090 GPU. For the tillage boundary detection dataset, various data are required for the construction of the solid model [15-18]. To this end, we collected the images by considering various environments reflecting sunny days, cloudy days, morning, afternoon, and different tillage fields. The data acquisition scenario using the tractor is described in Fig. 6. Our custom dataset consists of 1259 training and 697 test sets. Each image resolution is 320 × 240 pixels, and the Ground truth points for the tillage boundary consist of three points (See Fig. 4). Each tillage boundary point was annotated and validated by three

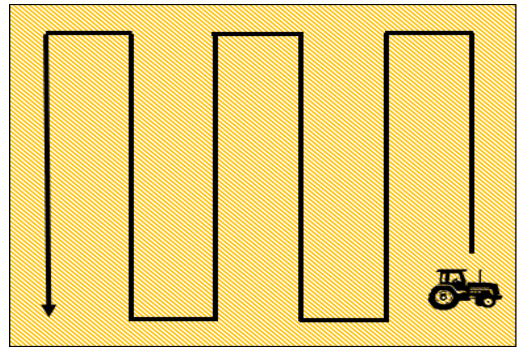

Fig. 6. A visualization of data collection route by tractor

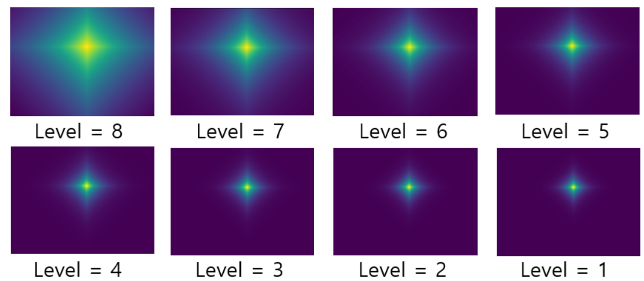

Fig. 7. A visualization of heatmaps according to scale levels

Fig. 8. A visual result of the tillage boundary points using the proposed method.

experts. For the evaluation, we used the Euclidean distance between predicted and Ground truth boundary points and Table 1 presents the performance of the proposed method according to Heatmap's scales. Note that Fig. 7 shows a visualization result of heatmaps according to scale levels. As the Heatmap scale increase, the network model learns the global patterns of the tillage lines; however, this leads to precision decreases. On the other hand, small scale tends to ignore the global context representations. Our model with Heatmap level 4 yields competitive performance. The visualization results of the tillage boundary point localization are illustrated in Fig. 8

.

4 CONCLUSIONS

In this paper, we proposed the heatmap regression-based tillage boundary detection method. To this end, we constructed the custom tillage boundary detection dataset. Unlike the existing methods, our model can detect the tillage boundary points easily without complex and heuristic post-process algorithms. Therefore, our model is quite robust to local noises. In the experimental results, the proposed method yields the competitive performance and computational efficiency. In future work, we plan to increase our custom dataset by considering various tillage environments, including newly added fields. We also continue to enhance the performance and architecture of our tillage boundary detection model with the newly added challenging dataset.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2021R1G1A1093546).

REFERENCES

[1] Kim, Y. J., Chung, S. O., & Choi, C. H. (2018). Development of automation technology for manual transmission of a 50 HP autonomous tractor. IFAC-Papers OnLine, 51(17), 20-22
[2] Li, M., Imou, K., Wakabayashi, K., & Yokoyama, S. (2009). Review of research on agricultural vehicle autonomous guidance. International Journal of Agricultural and Biological Engineering, 2(3), 1-16.
[3] Chen, H., Chen, A., Xu, L., Xie, H., Qiao, H., Lin, Q., & Cai, K. (2020). A deep learning CNN architecture applied in smart near-infrared analysis of water pollution for agricultural irrigation resources. Agricultural Water Management, 240, 106303.
[4] Kim, W. S., Lee, D. H., Kim, T., Kim, G., Kim, H., Sim, T., & Kim, Y. J. (2021). One-shot classification-based tilled soil region segmentation for boundary guidance in autonomous tillage. Computers and Electronics in Agriculture, 189, 106371.
[5] Liu, Y., Ma, X., Shu, L., Hancke, G. P., & Abu-Mahfouz, A. M. (2020). From Industry 4.0 to Agriculture 4.0: Current status, enabling technologies, and research challenges. IEEE Transactions on Industrial Informatics, 17(6), 4322-4334.
[6] Abdalla, A., Cen, H., Wan, L., Mehmood, K., & He, Y. (2020). Nutrient status diagnosis of infield oilseed rape via deep learning-enabled dynamic model. IEEE Transactions on Industrial Informatics, 17(6), 4379-4389.
[7] Wang, D., Zhang, D., Yang, G., Xu, B., Luo, Y., & Yang, X. (2021). SSRNet: In-field counting wheat ears using multi-stage convolutional neural network. IEEE Transactions on Geoscience and Remote Sensing, 60, 1-11.
[8] Su, J., Yi, D., Su, B., Mi, Z., Liu, C., Hu, X., ... & Chen, W. H. (2020). Aerial visual perception in smart farming: Field study of wheat yellow rust monitoring. IEEE transactions on industrial informatics, 17(3), 2242-2249.
[9] Kim, W. S., Lee, D. H., Kim, Y. J., Kim, T., & Lee, H. J. (2020). Path detection for autonomous traveling in orchards using patch-based CNN. Computers and Electronics in Agriculture, 175, 105620.
[10] Cai, K., Chen, H., Ai, W., Miao, X., Lin, Q., & Feng, Q. (2021). Feedback convolutional network for intelligent data fusion based on near-infrared collaborative IoT technology. IEEE Transactions on Industrial Informatics, 18(2), 1200-1209.
[11] Bakker, T., van Asselt, K., Bontsema, J., Müller, J., & van Straten, G. (2011). Autonomous navigation using a robot platform in a sugar beet field. Biosystems Engineering, 109(4), 357-368.
[12] Kim, G., Seo, D., Kim, K. C., Hong, Y., Lee, M., Lee, S., ... & Lee, D. H. (2020). Tillage boundary detection based on RGB imagery classification for an autonomous tractor. Korean Journal of Agricultural Science, 47(2), 205-217.
[13] D.-S. Seo, J.-H. Won, C.-Y. Yang, G.-K. Kim, K.-D. Kwon, K.-C. Kim, Y.-K. Hong, and H.-S. Ryu, "Development of Boundary Detection Methods Based on Images for Path Following of Autonomous Tractor," J. Korean. Inst. Comm. Inf. Sci., vol. 46, no. 11, pp.2078-2087, 2021
[14] Ronneberger, O., Fischer, P., & Brox, T. (2015, October). U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention (pp. 234-241). Springer, Cham.
[15] Paszke, A., Chaurasia, A., Kim, S., & Culurciello, E. (2016). Enet: A deep neural network architecture for real-time semantic segmentation. arXiv preprint arXiv:1606.02147.
[16] Pan, X., Shi, J., Luo, P., Wang, X., & Tang, X. (2018, April). Spatial as deep: Spatial cnn for traffic scene understanding. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 32, No. 1).
[17] Yu, F., Xian, W., Chen, Y., Liu, F., Liao, M., Madhavan, V., & Darrell, T. (2018). Bdd100k: A diverse driving video database with scalable annotation tooling. arXiv preprint arXiv:1805.04687, 2(5), 6.
[18] Geiger, A., Lenz, P., Stiller, C., & Urtasun, R. (2013). Vision meets robotics: The kitti dataset. The International Journal of Robotics Research, 32(11), 1231-1237.