

Title	Vision-based uncut crop edge detection for automated guidance of head-feeding combine
Author(s)	Cho, Wonjae; Iida, Michihisa; Suguri, Masahiko; Masuda, Ryohei; Kurita, Hiroki
Citation	Engineering in Agriculture, Environment and Food (2014), 7(2): 97-102
Issue Date	2014-04
URL	http://hdl.handle.net/2433/189414
Right	© 2014 Asian Agricultural and Biological Engineering Association. Published by Elsevier B.V.
Type	Journal Article
Textversion	author

Vision-based Uncut Crop Edge Detection for Automated Guidance of Head-Feeding Combine

Wonjae CHO^{*1}, Michihisa IIDA^{*2}, Masahiko SUGURI^{*3},
Ryohei MASUDA^{*3}, Hiroki KURITA^{*3}

Abstract

This study proposes a vision-based uncut crop edge detection method to be utilized as a part of an automated guidance system for a head-feeding combine harvester, which is widely used in Japan for the harvesting of rice and wheat. The proposed method removes the perspective effects of the acquired images by inverse perspective mapping and recovers the crop rows to their actual parallel states. Then, the uncut crop edges are detected by applying color transformation and the edge detection method. The proposed method has shown outstanding detection performance on the images acquired under various conditions of the paddy field with an average accuracy of 97% and a processing speed of 33 ms per frame.

[Keywords] Head-feeding combine harvester, Uncut crop edge detection, Inverse perspective mapping, Color transformation

I Introduction

1 Operation of a harvester in the field is demanding for
2 the operator because the work is time-consuming and to
3 deteriorates the health of the operator owing to, dust
4 particles as well as the noise and vibrations of the
5 harvesting machine. Moreover, the steering operation
6 requires the operator to possess a high level of
7 proficiency to compensate for the inefficiencies of
8 inaccurate steering, which could result in incompletely
9 harvested areas or re-harvesting of the areas. To address
10 such issues, automated guidance systems can steer
11 automatically by the edges of uncut crops to fully
12 complete the demanding tasks.

13 Because the automated guidance system provides an
14 optimal steering path after considering the machinery
15 environment, it reduces operator fatigue and improves
16 both safety and productivity of the operations. The
17 automated guidance system consists of two parts
18 including an autonomous system and an operator-
19 assisted system (Kise, *et al.*, 2005). The autonomous
20 system replaces the role of the operator in the field and
21 performs all operations, completing the harvesting task
22 automatically. The operator-assisted system merely
23 assists the operator and guides the machinery toward the
24 desired path. Although the two systems differ in
25 functionality, both perform path planning by navigation
26

27 sensors mounted on the machinery. The automated
28 guidance system of the harvesting machine repeats the
29 following process until harvesting is complete: The
30 current position of the machinery is first estimated in
31 real-time, and the course direction is determined by the
32 extraction of the uncut crop edges. Next, an optimal path
33 with minimum time consumption that does not damage
34 the crops is planned for the steering. Finally, the
35 machinery is steered along the desired path. As
36 previously described, because the automated guidance
37 system performs path planning and accurate steering on
38 the basis of the uncut crop edges extracted by the use of
39 navigation sensors mounted on the machinery, precise
40 extraction of the edges is critical to the system
41 performance.

42 In recent years, various sensor methodologies have
43 been proposed or developed for automated guidance
44 systems of harvesting machines. Researchers from the
45 National Agricultural Research Center in Japan and
46 Mitsubishi Farm Machinery Co., Ltd. have developed an
47 automatic travelling control system that performs straight
48 -forward traveling movement by detecting uncut crops
49 and incorporating a 90° turn by using the gyroscope
50 mounted on the combine body when the harvester
51 reaches the end of crop row. This action is performed by
52 utilizing the contact sensor mounted on the header's
53 divider of the head-feeding combine harvester (Sato, *et*

*1 JSAM Student Member, Graduate School of Agriculture, Kyoto University, Kitashirakawa Oiwake-cho, Sakyo-ku, Kyoto, 606-8502, Japan; cho@elam.kais.kyoto-u.ac.jp

*2 JSAM Member, Corresponding author, Graduate School of Agriculture, Kyoto University, Kitashirakawa Oiwake-cho, Sakyo-ku, Kyoto, 606-8502, Japan; iida@elam.kais.kyoto-u.ac.jp

*3 JSAM Member, Graduate School of Agriculture, Kyoto University, Kitashirakawa Oiwake-cho, Sakyo-ku, Kyoto, 606-8502, Japan

1 *al.*, 1996). Researchers from Carnegie Mellon University
 2 and the National Aeronautic and Space Administration
 3 (NASA) developed an automated guidance system that
 4 employs a color camera to extract the uncut crop edges
 5 to perform the automatic guiding task. This system was
 6 tested on a New Holland hay windrower and has
 7 successfully performed a harvesting task in an alfalfa
 8 field (Ollis and Stentz, 1997). Researchers from
 9 Cemagref Institute in France proposed an automatic
 10 guidance method for agricultural vehicles in either a
 11 structured environment, such as a windrow harvester, or
 12 an iterative structured environment, such as a combine
 13 harvester, by implementing a 1D scanning laser range
 14 finder (Chateau, *et al.*, 2000). Benson, *et al.* (2003)
 15 developed and demonstrated a machine-vision-based
 16 guidance system for small-grain harvesters with the use
 17 of a monochrome camera mounted on the machinery cab.
 18 Rovira-Más, *et al.* (2007) developed an autonomous
 19 guidance system that extracts the edges of uncut crops on
 20 the basis of 3D information obtained from stereo vision.

21 This study proposes a vision-based uncut crop edge
 22 detection method for an automated guidance system that
 23 can be utilized for a head-feeding combine harvester,
 24 which is widely used in Japan for harvesting rice and
 25 wheat. The proposed method detected the uncut crop
 26 edges a processing speed of 33 ms per frame in the
 27 paddy field under the conditions of various noise
 28 elements, shadows casted by irregular crop distribution
 29 and the driving direction of the combine harvester as
 30 well as dust particles generated by harvesting. Moreover,
 31 unlike previous researchers who detect uncut crop edges
 32 without removing the perspective effect existing on the
 33 images acquired from a single vision sensor (Ollis and
 34 Stentz, 1997; Benson, *et al.*, 2003), the present study
 35 identifies the relative lateral distance of the uncut crop
 36 edge from the center of origin of the vision sensor
 37 because this way it extracts the uncut crop edges by
 38 applying the inverse perspective mapping (IPM)
 39 algorithm to an image that uses the extrinsic and intrinsic
 40 parameters of the single-vision sensor. This process
 41 removes the perspective effect existing within the images
 42 and converts the location information of the image plane
 43 to that of the world coordinate system.

44

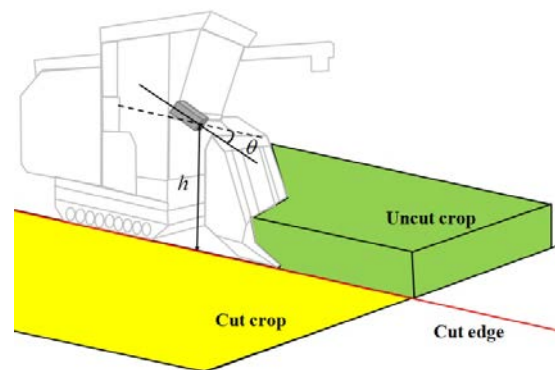
45 II Materials and Methods

46 1. Experimental setup

47 A VY446LM model head-feeding combine harvester
 48 (Mitsubishi Agricultural Machinery Co., Ltd., Japan) was
 49 used for experiments in this study. This harvester can

50 simultaneously harvest four rows of rice in a paddy field.
 51 The harvester driven by a human operator harvested rice
 52 at a speed of 0.8 m/s. The Microsoft LifeCam Studio
 53 vision sensor (Microsoft Co., Ltd.), which supports the
 54 USB 2.0 interface, was used for uncut crop edge
 55 detection. The vision sensor operates within a
 56 temperature range of 0 °C to 40 °C and a relative
 57 humidity range of 5% to 80%. A complementary
 58 metal-oxide semiconductor image sensor was used,
 59 which has a field of view of 75°. The sensor captures
 60 frames of color images in 640 pixel (horizontal) by 480
 61 pixel (vertical) resolution per second. As shown in Fig. 1,
 62 the camera is mounted on the frame located at the front
 63 of the cab of the head-feeding combine harvester. The
 64 center of the lens is located 1.5m vertically (h) from the
 65 ground, with a tilt angle (θ) of 10°. A computer with
 66 Corei5 CPU 2.40 GHz and 4GB memory was used.

67 This study utilized the machine vision function of the
 68 integrated sensor control platform (ISCP) for combine
 69 harvesters, which is currently under development for the
 70 implementation of a vision-based guidance method.
 71 ISCP supports various types of navigation sensors such
 72 as machine vision, laser range finder, and global
 73 positioning system (GPS), which are used for the
 74 automated guidance system of the combine harvester.
 75 This platform can also express graphic user interface
 76 (GUI)-based real-time data. Moreover, the open-source
 77 platform can freely be modified and re-distributed
 78 without license restrictions. The proposed vision-based
 79 guidance method was developed by using Visual C#
 80 language, and the open source computer vision (OpenCV)
 81 library was utilized for image processing.



82

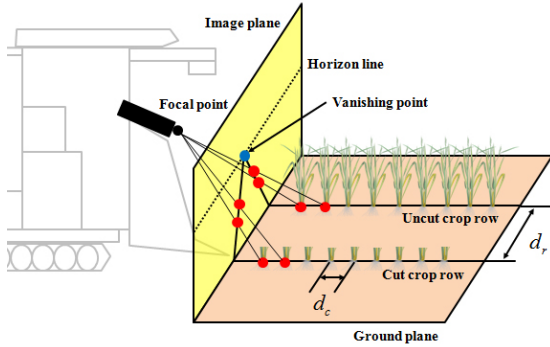
83 Fig. 1. Coordinate system of the camera mounted on the
 84 combine harvester.

85

86 2. Inverse perspective mapping

87 In the paddy fields of Japan, rice plants are evenly
 88 planted at approximately 0.3 m in the inter-row (d_r) and
 89 approximately 0.15 m in the intra-row (d_c) in a parallel

1 row formation. However, owing to the perspective effect,
2 the crop rows shown in the image planes acquired by the
3 camera are not shown in parallel formation but rather as
4 rows that converge to a single vanishing point, as shown
5 in Fig. 2.



7 Fig. 2. Geometry of the central projective model.

8
9
10 For the purpose of this study, IPM was utilized to
11 remove the perspective effect and restore the crop rows
12 to their original parallel state. IPM is a technique that
13 geometrically transforms an image by constructing a new
14 image on inverse 2D planar by projecting each of the
15 pixels of a 3D object in 2D perspective view and
16 remapping them to new positions (Bertozzi and Broggi,
17 1998). IPM removes the perspective effect by the use of
18 intrinsic (angular aperture and resolution) and extrinsic
19 (pitch angle, yaw angle, and height above ground)
20 parameters of the camera. It also has the ability to
21 calculate lateral distances between the crop rows from
22 the point of origin of the camera because it converts the
23 position information of the image plane to that of the
24 world coordinate system. IPM, in the mathematical sense,
25 is a transformation of a 3D Euclidean space, $W =$
26 $\{(x, y, z)\} \in E^3$ (world space), into a 2D Euclidean
27 space, $I = \{(u, v)\} \in E^2$ (image space). Whereas
28 Space I corresponds to the image acquired, the
29 remapped image is defined under the flatness assumption
30 on the xy plane of Space W , namely the $S \triangleq$
31 $\{(x, y, 0)\} \in W$ surface. Fig. 3 shows the extrinsic
32 parameters of the camera mounted on the combine
33 harvester. Parameters $\bar{\gamma}$, $\bar{\theta}$, and h denote the yaw angle,
34 pitch angle, and the height of the camera from the
35 ground, respectively, and l and d represent the
36 longitudinal and transverse distances of the camera to the
37 center of origin on the xy plane. The intrinsic
38 parameters are expressed as the angular aperture 2α
39 and resolution $m \times n$. By using the extrinsic and intrinsic
40 parameters, the mapping function from Space I to
41 Space S can be defined as in Eq. (1): ($f: I \rightarrow S$).

$$x(u, v) = h \times \cot[(\bar{\theta} - \alpha) + u \frac{2\alpha}{n-1}]$$

$$\times \cos[(\bar{\gamma} - \alpha) + v \frac{2\alpha}{m-1}] + l$$

$$y(u, v) = h \times \cot[(\bar{\theta} - \alpha) + u \frac{2\alpha}{n-1}]$$

$$\times \sin[(\bar{\gamma} - \alpha) + v \frac{2\alpha}{m-1}] + d$$

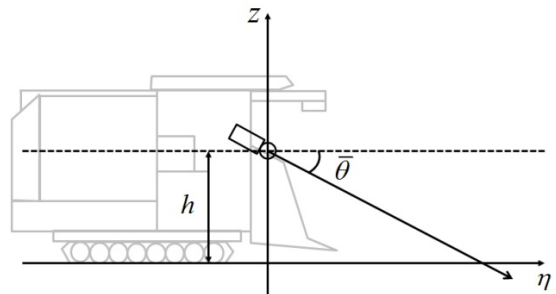
$$z(u, v) = 0$$

42
43 Moreover, Eq. (2) defines the projection
44 transformation used to remove the perspective effect,
45 which recovers the texture of the S surface (the $z = 0$
46 plane in Space W).

$$u(x, y, 0) = \frac{\arctan \left\{ \frac{h \sin \left[\arctan \left(\frac{y-d}{x-l} \right) \right]}{y-d} \right\} - (\bar{\theta} - \alpha)}{\frac{2\alpha}{n-1}}$$

$$v(x, y, 0) = \frac{\arctan \left[\frac{y-d}{x-l} \right] - (\bar{\gamma} - \alpha)}{\frac{2\alpha}{m-1}}$$

47
48
49 Each pixel scanned from the coordinates $(x, y, 0) \in$
50 W , which forms the remapped image, is assigned the
51 value of its corresponding pixel in the coordinates
52 $(u(x, y, 0), v(x, y, 0)) \in I$. Once these two equations are
53 applied, the window of interest from the input image can
54 be projected onto the ground plane. Fig. 4 shows the
55 original image acquired from the camera and the image
56 transformed by the IPM algorithm. The original image
57 (640×480 pixels) is shown in Fig. 4(a), with the
58 region of interest (ROI; 640×400 pixels) shown in the
59 square (red); the transformed IPM image (320×240
60 pixels) is shown in Fig. 4(b). As indicated in the figure,
61 the IPM image shows the crop rows in fixed width
62 intervals as vertical, straight lines in a parallel
63 configuration.



65
66 (a) $z\eta$ plane.

67

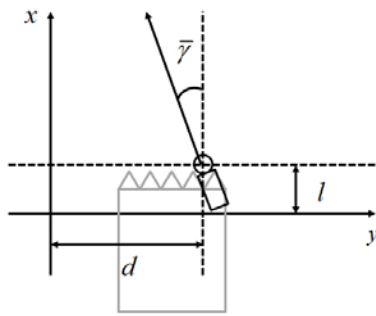
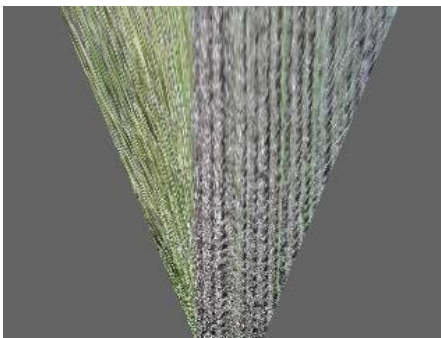
(b) xy plane.

Fig. 3. Extrinsic parameters of the camera.



(a) Input image, the region of interest marked off.



(b) Inverse perspective mapping (IPM) view.

Fig. 4. Original image and the converted inverse perspective mapping (IPM) image.

3. Color space transformation

The IPM images, transformed in the RGB color space, contain the surrounding information about shadows, dust particles floating in air, and any potential noise that might have been generated as the result of radical brightness changes in the surroundings. Therefore, prior to applying the uncut crop edge detection algorithm, a robust segmentation method is required to filter out the noise in the images and extract the uncut crop areas. Under this backdrop, color indices have been developed that can distinguish crops from other image elements (Woebbecke, *et al.*, 1995; Meyer, *et al.*, 1998; Kataoka, *et al.*, 2003; Neto, 2004; Hague, *et al.*, 2006). By the

24 image transformation into these indices, the spectral
25 differences between plants and the rest of the image
26 areas are contrasted. In the present study, the excess
27 green minus excess blue index (ExGB), based on the
28 visible spectral indices proposed by early researchers,
29 has been applied to the images to perform segmentations.
30 ExGB is defined as

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B} \quad (3)$$

$$\text{Excess green: ExG} = 2g - r - b$$

$$\text{Excess blue: ExB} = 1.4b - g$$

$$\text{Excess green minus excess blue: ExGB} = \text{ExG} - \text{ExB}$$

32 where R, G, and B are normalized RGB coordinates that
33 range from 0 to 1. They are obtained from Eq.(4):

$$R = \frac{R}{R_{max}}, G = \frac{G}{G_{max}}, B = \frac{B}{B_{max}} \quad (4)$$

35 where $R_{max} = G_{max} = B_{max} = 255$ (for 24-bit color
36 images). Thus, on the basis of normalized RGB
37 coordinates, these indices become insensitive to the
38 changes that arise from ambient light conditions as well
39 as to the differences in the angles to target surfaces. Fig.
40 5 shows the results of the uncut crop segmentation by
41 applying the ExGB method to transformed IPM images.
42 In the grayscale-converted ExGB images, it is likely that
43 the higher pixel values represent uncut crop areas and
44 that the lower values indicate harvested crops or image
45 noise.

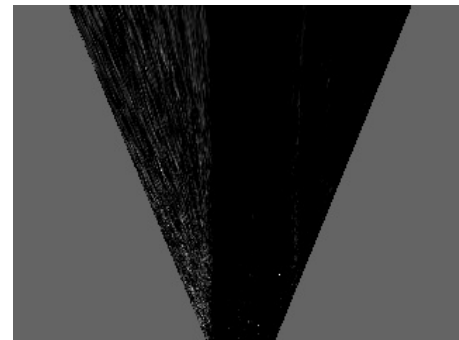


Fig. 5. Excess green minus excess blue index (ExGB) image.

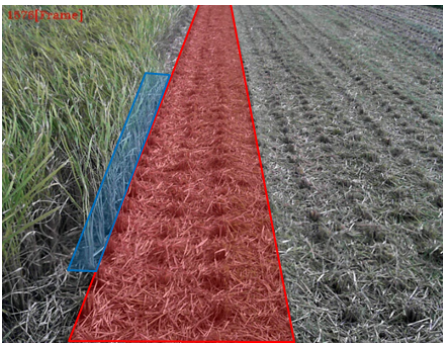
4. Uncut crop edge detection

51 The precise steering of a harvesting machine along
52 uncut crop edges would leave no uncut crops in the rows
53 from the previous harvesting path as shown in Fig. 6(a).
54 However, if the steering is not precise, there would be
55 uncut remains in the crop rows from the harvesting path,
56 as shown in Fig. 6(b). In such cases, unless the next
57 harvesting path is determined by detection of the uncut
58 crop edges of the previous harvest path, re-harvesting is

- 1 required after the completion of the overall harvesting,
 2 which would decrease the harvest efficiency.



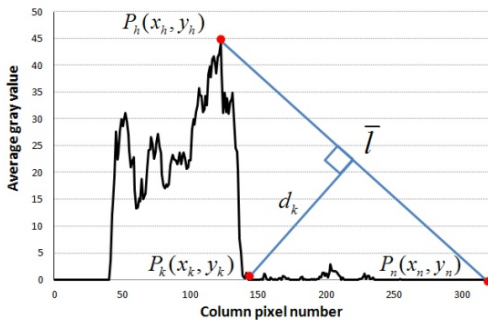
3 (a) No uncut crops after precise steering



4 (b) Remaining uncut crops after imprecise steering.

5 Fig. 6. Uncut crop remainders in planned harvest paths
 6 due to differences in steering performance.

7
 8
 9
 10 Therefore, in this study, the outer-most boundary point
 11 of the uncut crop area is detected from the image for
 12 configuring the uncut crop edge. In this process, two
 13 techniques are applied. ExGB images are first scanned
 14 left to right for each row. The average gray level for each
 15 column is then calculated and stored in an array of $S =$
 16 $\{p_i | i = 1, \dots, n\}$; n is number of columns. Fig. 7 shows
 17 the average distribution of the gray level for the pixels of
 18 each column; the abscissa is the number of columns for
 19 the grayscale image, and the vertical axis is the average
 20 pixel gray level for each column.

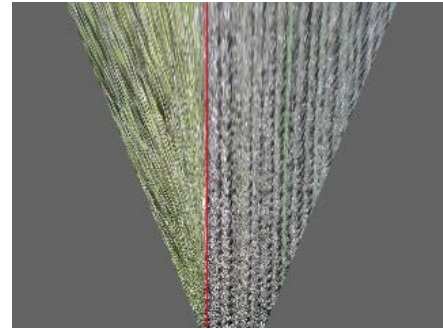


21
 22 Fig. 7. Average distribution of the gray level value per
 23 column pixels.
 24

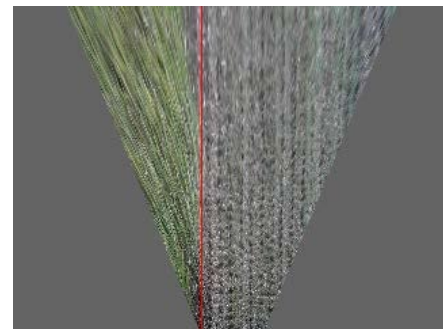
25 Because harvesting was performed counter-clockwise
 26 in the course of this study, the uncut crop area is located
 27 on the left side of the uncut crop edge in the acquired
 28 image, and the harvested area appears on the right.
 29 Leveraging on such characteristics, the line segment (\bar{l}),
 30 the connection between the maximum value of the
 31 average gray level (p_h) and the end point (p_n) within
 32 dataset S is calculated. Then, the point (p_k), in which
 33 the distance of the line perpendicular (d_k) to segment \bar{l}
 34 from data set $V = \{p_i | i = h, \dots, n\}$ reaches the
 35 maximum, is calculated by Eq. (5) (Kimberling, 1998) .

$$36 \quad d_k = \frac{|(x_n - x_h)(y_h - y_k) - (x_h - x_k)(y_n - y_h)|}{\sqrt{(x_n - x_h)^2 + (y_n - y_h)^2}} \quad (5)$$

37 Because the x value of the calculated p_k represents
 38 the outer-most boundary point of the uncut area, the
 39 uncut and harvested areas can be distinguished from the
 40 image on the basis of this value. Fig. 8 shows the results
 41 of the application of the proposed methods to Fig. 6(a)
 42 and Fig. 6(b). Because the proposed detection method
 43 defines the uncut crop edges on the basis of the
 44 outer-most boundary point of the uncut area, it can
 45 ideally and accurately detect the edges from that shown
 46 in Fig. 6(a), in which the previous harvest is precisely
 47 completed, and for that shown in Fig. 6(b), in which
 48 uncut remainders exist in the crops rows of the previous
 49 harvest.



50 (a) Edge detection in Fig. 6(a).



51 (b) Edge detection in Fig. 6(b).

52 Fig. 8. Successful uncut crop edge detection.
 53
 54
 55
 56

III Results and Discussion

For the evaluation of the outdoor performance of the proposed method, actual rice harvesting images from a rice paddy field in Nantan City, Kyoto Prefecture, Japan, were acquired under sunny conditions. *Oryza sativa L.* (cv. *Kinu-hikari*) was the crop harvested for the experiment. As a human operator steered the combine harvester, the scenes were stored and saved in video format (Audio Video Interleave). Because the combine harvester travelled counter-clockwise during the harvesting period, as shown in Fig. 9, the noise levels in the acquired images differ as the light conditions changed depending on the movement direction.

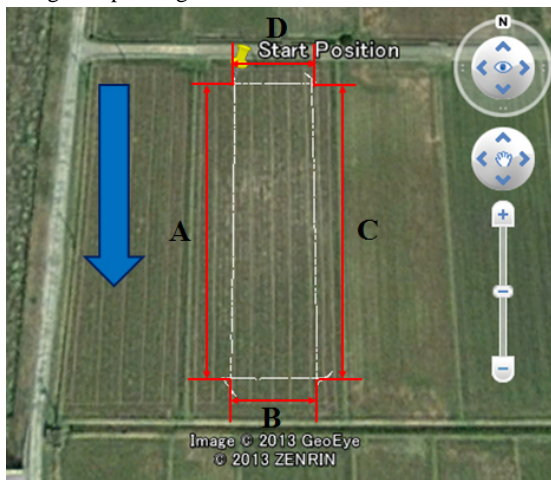


Fig. 9. Travelling path of the combine harvester obtained from Google Maps.

For easier comparison of the results, all of the acquired images were categorized into four datasets, according to the directions of the harvester movement, as shown in Table 1. The success of the uncut crop edge detection was determined through human eye perception. The video results can be accessed at <http://youtu.be/wJ5u850aQII>.

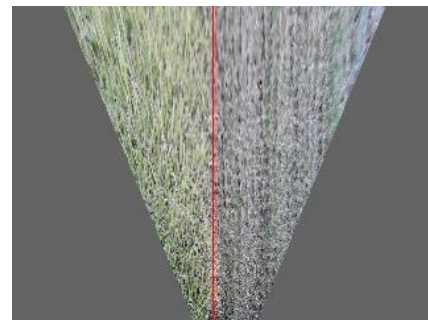
Table 1 Results determined by the proposed method.

Dataset	Movement direction	Frames	Success Rate [%]
A	South	950	100
B	East	300	100
C	North	950	94
D	West	300	100

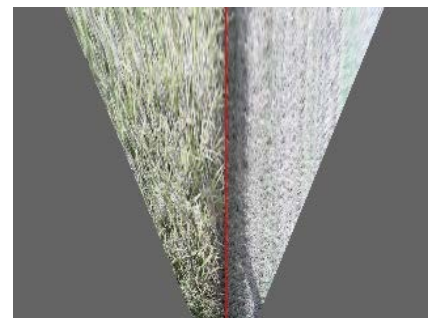
The evaluation results show that the proposed method is effective in detecting the uncut crop edges from the images under various conditions. The average detection accuracy of the uncut crop edge by the proposed method was 97% at an average processing speed of 33 ms per

frame. The evaluation results show that the proposed method can detect the edges of the uncut crops with relatively high accuracy regardless of to the movement direction of the combine harvest or the noise from the surrounding conditions, as shown in Fig. 10.

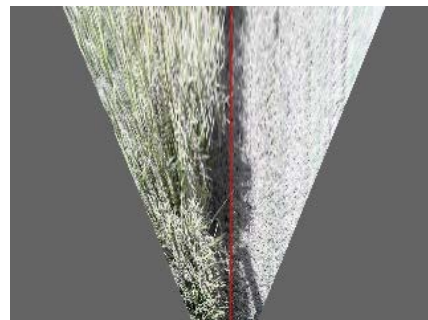
However, as shown in Fig. 11(a), in which the combine harvester was heading north (dataset C), the uncut crop detection was not successful owing to the combination of image information including shadows cast by the machine and the uncut crops and the random patterns of uncut crops left in the previous harvesting path. Of course, because uncut crop edges were successfully detected in Fig. 11(b), the image was consecutively acquired after Fig. 11(a), the detection can be corrected by adjusting the guidance path by steering. However, it is likely that the rapid steering of the combine harvester may cause uncut crops to remain in the rows of the previous harvest paths. Therefore, an algorithm to calibrate and adjust the failures in detecting uncut crop edges should be developed.



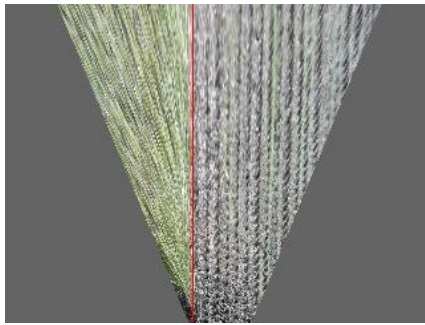
(a) Facing the sun.



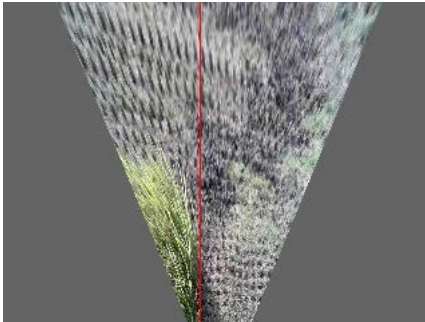
(b) Back to sun and shadow.



(c) Random uncut crop distribution.

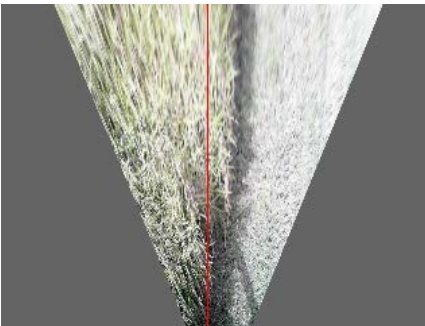


(d) Beginnig of harvest.

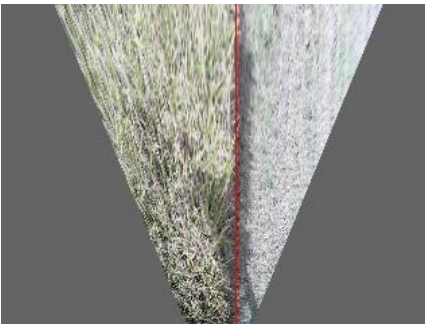


(e) End of harvest.

Fig. 10. Results of uncut crop edge detection under various experimental conditions.



(a) Before, unsuccessful detection of uncut crop edge.



(b) After, Successfully detection of uncut crop edge.

Fig. 11. Detection results in consecutively acquired images.

IV Summary and Conclusions

This study proposed a robust, efficient, and real-time method for the detection of uncut crop edges to be

utilized in paddy fields. The proposed method acquires top view images of the field, which are then filtered with ExGB and uncut edge detection algorithms. The tested method detected nearly all uncut crop edges, as shown in still images of the paddy field, and performed image processing at a speed of 33 ms per frame. However, its performance was poor under certain environmental conditions. Thus, a new algorithm to calibrate and adjust such failures in uncut crop edge detection should be developed. Moreover, future developments should consider methods for providing robust guidance by the use of vision sensors together with other navigation sensors, such as GPS or laser range finders.

References

- Benson, E. R., J. F. Reid and Q. Zhang. 2003. Machine vision-based guidance system for agricultural grain harvesters using cut-edge detection. *Biosystems Engineering* 86(4): 389-398.
- Bertozzi, M. and A. Broggi. 1998. GOLD: A parallel real-time stereo vision system for generic obstacle and lane detection. *IEEE Transactions on Image Processing* 7(1): 62-81.
- Chateau, T., C. Debain, F. Collange, L. Trassoudaine and J. Alizon. 2000. Automatic guidance of agricultural vehicles using a laser sensor. *Computers and Electronics in Agriculture* 28(3): 243-257.
- Hague, T., N. D. Tillett and H. Wheeler. 2006. Automated crop and weed monitoring in widely spaced cereals. *Precision Agriculture* 7(1): 21-32.
- Kataoka, T., T. Kaneko, H. Okamoto and S. Hata. 2003. Crop growth estimation system using machine vision. In Proc. IEEE/ASME International Conference on Advanced Intelligent Mechatronics, b1079-b1083.
- Kimberling, C. 1998. Triangle centers and central triangles. Utilitas Mathematica Publishing, Inc.
- Kise, M., Q. Zhang and F. Rovira Más. 2005. A stereovision-based crop row detection method for tractor-automated guidance. *Biosystems Engineering* 90(4): 357-367.
- Meyer, G. E., T. Mehta, M. F. Kocher, D. A. Mortensen and A. Samal. 1998. Textural imaging and discriminant analysis for distinguishing weeds for spot spraying. *Transactions of the ASAE* 41(4): 1189-1197.
- Neto, J. C. 2004. A combined statistical-soft computing approach for classification and mapping weed species in minimum-tillage systems. University of Nebraska, Lincoln, NE.
- Ollis, M. and A. Stentz. 1997. Vision-based perception for an automated harvester. In Proc. IEEE/RSJ International

- 1 Conference on Intelligent Robots and Systems, 1838-1844.
2 September.
- 3 Rovira-Más, F., S. Han, J. Wei and J. F. Reid. 2007.
4 Autonomous guidance of a corn harvester using stereo
5 vision. *Agricultural Engineering International: the CIGR*
6 *Ejournal* 9.
- 7 Sato, J., K. Shigeta and Y. Nagasaka. 1996. Automatic operation
8 of a combined harvester in a rice field. In *Proc.*
9 *IEEE/SICE/RSJ International Conference on Multisensor*
10 *Fusion and Integration for Intelligent Systems*, 86-92.
11 Washington, DC, 8-11 December.
- 12 Woebbecke, D. M., G. E. Meyer, K. Von Bargen and D. A.
13 Mortensen. 1995. Color indices for weed identification
14 under various soil, residue, and lighting conditions.
15 *Transactions of the ASAE* 38(1): 259-269.
- 16 (Received : X. January. 20XX, Accepted : X. February. 20XX)