Review on Application of Binocular Vision Technology in Field Obstacle Detection

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Abstract: Obstacles within the field are the main external source of safety hazard in field operation of agricultural machineries. Autonomous obstacle avoidance is a critical technology to be solved for the robotization of field operation by agricultural machineries. For this technology, a critical premise is to timely and accurately perceive static and dynamic information of field obstacles. Whereafter, compared with other detection technologies, applicability of binocular vision-based detection technology in field obstacle detection is analyzed. Afterwards, this paper summarizes the whole process of binocular vision-based obstacle detection into three steps. For step one, main detecting methods for locating obstacles in images, main principles of these methods and their applicability in field operation scene are discussed. For step two, main existing methods for detecting spatial position parameters of obstacles based on detection results of step one and their application status in field operation scene are summarized. For step three, typical target tracking methods for obtaining the motion state of obstacles are compared and summarized, and their reference value for future research is pointed out. At last, the main challenges of detecting obstacles in field scene based on binocular vision are summarized.

1. Introduction

The robotization of field operation is an indispensable part of the robotization of agricultural production, which is of great significance for solving the shortage of agricultural labor force, promoting targeted and intellectualized agricultural machineries and improving efficiency and economic benefits of agricultural production. From the current view, the whole-process autonomous navigation walking technology of agricultural machinery in the non-structured field operation environment is one of the key technical bottlenecks for achieving the transition from automation to robotization of field operation.

For the whole-process autonomous navigation walking of agricultural machinery (mainly referring to the large-scale conventional agricultural machinery in this paper) during field operation, it mainly includes the following three parts of walking process: autonomous navigation walking during normal operation in the field, autonomous turning at the end of field, and autonomous obstacle avoidance when encountering obstacles in field. Among them, the walking process of autonomous obstacle avoidance, which is usually manifested as conditional stress behavior requiring real-time response and has random characteristics, is an important feedback mechanism responding to external safety hazards for agricultural machineries during field operation. Obviously, in order to realize this part of
autonomous walking process, the primary task is to timely sense obstacles in the field environment, especially obstacles within the coverage area of operation path in front of the current agricultural machinery, so as to obtain their overall dimensions, spatial position relative to the current agricultural machinery and their state of motion.

Besides, binocular stereo vision, which is similar to human binocular view and conforms to human habit of perception [1], can provide depth distance or three-dimensional information of obstacles in scenes based on the principle of distance measurement using binocular disparity by stereo matching, and its application in obstacle detection draws increasing attention of scholars worldwide. In view of this, this paper mainly focuses on an overview of the application status and development tendency of binocular stereo vision technology in field obstacle detection, so as to provide a systematic and comprehensive technical reference and information support for further development and improvement of related algorithms.

2. Main detection parameters of field obstacles
For a single target obstacle, whether static or dynamic obstacle, main detection parameters include two types of static parameters - its spatial position relative to the machinery described by two parameters of depth distance and azimuth angle, and its dimensions of two-dimensional projected contour described by two dimensions of height and width/length – and dynamic parameters - magnitude and direction of its movement, of which, for static obstacles, the magnitude of their movement is regarded as 0. For a single target obstacle group merged from multiple target obstacles, main detection parameters are similar. As shown in Figure 1(a), when the machinery operates normally and arrives at the point O_E along the crop rows, the distance O_E shown in the figure is the depth distance of the current obstacle, the angle θ is the azimuth angle of the current obstacle, and the height and width of circumscribed rectangle as shown in Figure 1(b) are the dimensions of two-dimensional projected contour.

3. Advantages and disadvantages of binocular vision technology in detecting field obstacles
Current sensing technologies for detecting obstacles mainly include ultrasonic sensing [2] [3], laser radar sensing [4] [5], millimeter-wave radar sensing [6] [7], and binocular vision sensing [8] [9] and multiple-sensor fusion sensing[10][11]. Most of the current obstacle detection technologies focus on indoor environment or simple outdoor environment with known structure (e.g. structured road/highway or urban streets environment with favorable conditions), while the study on field environment is less performed [12]. Applicability in using a single type of sensing technology described above to detect obstacles in outdoor scenes [12] [13] [14] is compared, as shown in Table 1.

Relative to laser radar, millimeter-wave radar and ultrasonic sensor, binocular vision features light load and low cost, with passive measurement method and without emitting signals interfering each other. Moreover, it can provide abundant and dense 3D information (e.g., dimensions, colors, texture, depth distance, spatial position, etc.), and can detect obstacles in wider view, obstacles lower than the ground surface (that is, negative obstacles such as ditches, pits and pools) and obstacles lower than top of the crops but not completely covered. However, the current study on binocular vision-based obstacle detection mainly focuses on indoor environment or simple outdoor environment. In the actual unstructured and complicated field environment, affected by weather (e.g., dust, rain, snow or fog), natural light change and blowing dust during field operation, as well as random appearance of obstacles with various types, using binocular vision to rapidly identify obstacles in the field has been a research hotspot for scholars worldwide.

In accordance with Table 1, using a single type of sensor to sense obstacles in outdoor environment shows imperfections and can barely satisfy requirements of real-time capability and reliability. Meanwhile, multi-sensor fusion system usually taken vision sensor as one of main sensors for detecting obstacles in outdoor scenes draws increasing concern. However, although multi-sensor fusion technology may provide comprehensive and precise information, it brings comparatively complex structure, requires high costs and can’t ensure real-time capability.
4. **Application of binocular vision technology in field obstacle detection**

Different from obstacle recognition in whether structured or unstructured road scene, recognition of obstacles in field operation scene usually doesn’t require the recognition of the road area before detecting obstacles. In general, the field area in front of agricultural machinery during its operation is considered the area of interest with obstacles to be recognized by default, and obstacle detection may be directly performed in this area. In view of this, road recognition is not taken into consideration in this paper when discussing binocular vision-based obstacle detection methods in various scenes. Binocular vision-based obstacle detection mainly consists of three detection steps: step one – to locate target obstacles in images; step two – to locate target obstacles in three-dimensional space; step three – to obtain the motion state of target obstacles.

(a) Azimuth of obstacles relative to the machinery from the top view

(b) Dimensions of the two-dimensional projected contour of obstacles from the front view

**Figure 1 Schematic view of static detection parameters of target obstacles in the field**

Notes:
- $A_t, B_t, C_t, D_t$: four apexes of circumscribed rectangle of obstacle area in the top view. Where, the left and right sides of the rectangle are parallel to crop rows.
- $O_c$: midpoint of the side $A_tB_t$.
- $O_p$: a normal operating position point of the machinery before encountering obstacles, at which the operation direction is forward along the crop rows.
- $\theta$: azimuth angle of the current obstacle, which is the angle of $O_c$ deviated from normal operation direction when the machinery is at the position point $O_p$ during normal operation.
- $O_{cE}$: distance between $O_c$ and the operation point $O_p$ along normal operation direction, i.e. along the crop rows. When the agricultural machinery operates normally and arrives at the position point $O_p$, the distance $O_{cE}$ is the depth distance of the current obstacle relative to the machinery.
- $A_f, B_f, C_f, D_f$: four apexes of circumscribed rectangle of obstacle area in the front view. Where, the top and bottom sides of the rectangle are parallel to the horizon line. The actual dimensions of this circumscribed rectangle are the dimensions of the two-dimensional projected contour of the obstacles projected toward the machinery.
Table 1 Comparison of applicability of obstacle detection technologies in outdoor scenes, especially in unstructured and complicated field environment

| Technology       | Weight, cost and detection method                                                                 | Weather (dust/rain/snow/fog) and light (sunny/cloudy, day/night) influence | Detectable obstacles types, detectable parameters and detection distance | Timeliness and accuracy | Reference |
|------------------|--------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|--------------------------------------------------------------------------|-------------------------|-----------|
| Ultrasonic       | • Light weight                                                                                    | • Limited performance measurement. It may be influenced by air temperature and humidity | • Affected by the types of obstacle surface, it can’t detect obstacles mixed with crops, especially those lower than top of the crops. It can hardly identify obstacles lower than the ground surface. | • Speed of data acquisition and processing is fast enough for field scene. | [15][16] |
|                  | • Low cost                                                                                        | • Operation in any light                                                     | • Poor accuracy due to poor directionality, frequent misreadings and specular reflections |                        |           |
|                  | • Active sensor, with interference among multiple sensors, not well-suited for collaborative operation of multiple machineries |                                                                             | • Operation in any light                                                  |            |           |
|                  |                                                                                                  |                                                                             | • Operation in any light                                                  |            |           |
| Millimeter-wave  | • Light weight                                                                                    |                                                                             | • Operation in any light                                                  | • Speed of data acquisition and processing is fast enough for field scene. | [13][14] |
| radar            | • High cost,                                                                                    |                                                                             | • Operation in any light                                                  | • Accurate enough      |           |
|                  | • Active sensor, with interference among multiple sensors, not well-suited for collaborative operation of multiple machineries |                                                                             | • Operation in any light                                                  |            |           |
|                  |                                                                                                  |                                                                             | • Operation in any light                                                  |            |           |
|                  | • Heavy weight                                                                                    |                                                                             | • Decreased performance measurement                                    | • For field scene, speed of data acquisition and processing is fast enough for two-dimensional laser radar, but not well-suited for three-dimensional laser radar with low imaging speed. | [17][12] |
|                  | • Highest cost, especially three-dimensional laser radar                                           |                                                                             | • Operation in any light                                                  | • Accurate enough      |           |
|                  | • Active sensor, with interference among multiple sensors, not well-suited for collaborative operation of multiple machineries |                                                                             | • Operation in any light                                                  |            |           |
|                  |                                                                                                  |                                                                             | • Operation in any light                                                  |            |           |


Binocular vision
• Light weight
• Low cost
• Mainly passive sensors, with no interference among multiple passive sensors, provide abundant and dense 3D information, applicable to collaborative operation of multiple machineries

• Limited performance measurement in dust or fog environment, while less affected by rain or snow
• Affected by light change

• Limited, with satisfied detection accuracy within 10m, generally not exceeding 30m

• Short data acquisition cycle. Efficiency of data processing depends on the capabilities of image processing algorithm.
• Depend on image processing algorithm and decrease with the increase of distance.

4.1. Step one: to locate target obstacles in images
Binocular vision-based obstacle detection usually requires to locate target obstacles in the images first, that is, to extract target obstacle regions or their edge contour. Methods for such extraction work mainly include the following three types:

Type 1: locating obstacles in images based on monocular vision. To be specific, there are mainly three approaches. The principles of these approaches and their limitations in field operation scene are shown in Table 2.

Type 2: locating obstacles in images based on binocular disparity. To be specific, there are currently three approaches. The principles of these approaches and their applicability in field operation scene are shown in Table 2.

Type 3: locating obstacles in images by combining monocular and binocular vision. The principle and main advantages of this method in field operation scene are shown in Table 2.
Table 2 Methods used for step one and their applicability in field operation scene

| Main methods                      | Main approaches and principles                                                                                   | Applicability in field operation scene                                                                 | Reference |
|-----------------------------------|-----------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|-----------|
| **Monocular vision-based method** | Approach 1: Based on traditional characteristic analysis of colours, texture, morphology and edges.            | Applicable to detect specific types of obstacles with specific characteristics under a specific field scene, season, weather or light conditions. | [20][21] |
|                                   | Approach 2: Based on motion characteristics, such as methods of inter-frame difference, optical flow analysis, and motion compensation etc. | Affected by changeful posture and motion state of obstacles, light change, complicated and changeful field operation scene, etc. | [22][23] |
|                                   | Approach 3: Based on learning characteristics of neural network-based or support vector machine-based machine learning or deep learning. | In order to be applicable in complicated and changing field operation environment with diverse obstacle characteristics, it is necessary to collect a large number of training sample sets of obstacles with different characteristics under different field scenes, seasons, weather and light conditions. | [24][25] |
| **Binocular disparity-based method** | Approach 1: Based on inverse perspective transformation. Obtain non-zero disparity regions (i.e. obstacle area). | Applicable to detect obstacles on flat surface rather than in field operation scene.                     | [26][27] |
|                                   | Approach 2: Based on plane-line projection characteristics of UV-disparity. Obtain height of vertical line segments in V-disparity maps (i.e. height of obstacle area). Obtain length of horizontal line segments in U-disparity maps (i.e. width of obstacle area). | Applicable to detect obstacles with plane characteristics in normal structured road scene. Not well suitable in unstructured field operation scene without noticeable and fixed road characteristics but with complicated types of obstacles, especially obstacles lower than top of the crops and negative obstacles lower than the ground surface. | [28][9] |
| **Method of combining monocular and binocular vision** | Approach 3: Based on binocular stereo matching. Combined with edge and texture feature of disparity or depth map, or point cloud density feature of 3D point cloud map. Combined with limiting conditions such as distance range (e.g., taking nearby obstacles as target obstacles) and size dimensions determined by practical application. Combined with methods such as region clustering, etc. Obtain the area position or edge contour of the obstacles. | Precise stereo matching of image pairs in complicated and unstructured field scene is the most complicated and time-consuming part. Sensitive to regions with ambiguous or repeated texture which commonly appear in field scene, or occlusion by crops or other obstacles in the field. Difficult to detect obstacles with their characteristics similar to field background. Affect by geometric distortion, imaging distortion, view difference and natural light change, etc. Influence factors restricted its applicability in field scene cover the above related content. Determining candidate target zones in early stage can narrow down searching range during subsequent stereo matching, reduce complexity of matching algorithm, decrease computation load and improve real-time capability. | [29][30] |
|                                   | Preliminarily and respectively locate suspected obstacles in image pairs with the monocular vision-based method. Finally locate target obstacles of interest after removing false obstacles or currently subordinate obstacles with binocular disparity-based method. | | [31][32] |
4.2. Step two: to locate target obstacles in three-dimensional space

Obviously, it is far from being enough by just obtaining the position information of obstacles in images, and their location information relative to the subject of obstacle avoidance in three-dimensional space is actually the critical information truly needed in practical obstacle avoidance. On the basis of the principle of disparity in binocular stereo imaging system, especially extensively used parallel binocular stereo imaging system, depth distance of the characteristic points on the target relative to the camera can be easily obtained or their three-dimensional coordinate information can even be regained by combining triangulation method after obtaining internal and external parameters of the camera by binocular camera calibration and obtaining disparity information of matched pairs of the characteristic points by stereo matching. Therefore, on this basis, according to disparity information obtained by stereo matching of the overall target obstacle region [33] or its edge contour [34] or its characteristic points [35], three-dimensional reconstruction for the target obstacles may be performed to regain their spatial location and three-dimensional geometrical information.

Although three-dimensional point cloud data of the overall obstacle region or its edge contour can be obtained via three-dimensional reconstruction to provide more abundant and complete spatial azimuth information and three-dimensional contour information of obstacles for planning the obstacle avoidance path. Nonetheless, for obstacle avoidance during field operation of agricultural machineries, considering the regular field operation route of the machineries along the rows and the practical requirement for preventing damage to crops in their growing period, no matter for static or dynamic obstacles, only the following three spatial position parameters need to be detected as described in Section 2.2 in order to locate obstacles in three-dimensional space: depth distance, azimuth angle, dimensions of two-dimensional projected contour.

4.2.1. Detection of depth distance. In the above three parameters, detection of depth distance is fundamental and critical. Currently, detection of depth distance of obstacles has been extensively discussed in many papers.

If in step one, the target obstacle region or the edge contour of obstacles is located in respective left and right image pair with the monocular vision-based method, stereo matching may be performed for characteristic points (e.g. randomly selected points, angular points, centroid or center of mass) on the target region pairs [36] [37] or characteristic points (e.g., randomly selected points, discrete sampling points, vertexes or angular points) on the edge contour pairs [34] in step two to obtain respective disparities, and then the depth distance of the obstacles can be detected based on triangulation method.

If local position matching point pairs of target obstacles or area position or edge contour of target obstacles in the disparity map is obtained with the binocular disparity-based method or with the method of combing monocular and binocular vision in step one, the corresponding disparity information may be directly used to measure the depth distance of the target obstacles by triangulation method in step two [38]. If the area position or edge contour of obstacles in the depth map or three-dimensional map of point cloud are obtained in step one, the depth distance of the obstacles may be directly obtained in step two based on corresponding depth data or three-dimensional data [39].

4.2.2. Determination of azimuth angle. For determination of azimuth angle, generally, once three-dimensional coordinate information at the center of the obstacle region or center of its edge contour or center of the characteristic points on it is regained based on the principle of distance measurement by binocular disparity, information about the azimuth angle as well as the depth distance may be simply estimated [40].

4.2.3. Detection of dimensions of two-dimensional projected contour. For detection of dimensions of two-dimensional projected contour, if three-dimensional point cloud data of the overall obstacle region or its edge contour is regained based on the principle of distance measurement by binocular disparity, its three-dimensional contour dimensions, including dimensions of the two-dimensional projected contour.
contour and thickness information in the depth direction, can be obtained based on the difference between the maximum and the minimum values of point cloud data along each coordinate axis.

For the regular-shaped obstacle, only three-dimensional coordinate information of vertexes or angular points on obstacle region or its edge contour need to be regained in order to obtain three-dimensional contour dimensions of the obstacle [33][36].

In addition, if the circumscribed rectangle of obstacle region in original image is known, actual dimensions of the circumscribed rectangle may be calculated by combining depth distance with the triangulation method, or by regaining the three-dimensional coordinate information of two diagonal vertexes of the circumscribed rectangle or 4 points in obstacle region closest to four sides of the circumscribed rectangle based on the principle of distance measurement by binocular disparity [40]. Of which, if the vertexes are not within the obstacle region, disparity value within obstacle region will be regarded as disparity value of the vertexes. The dimensions of the circumscribed rectangle are approximate to the required dimensions of the two-dimensional projected contour.

Thus it can be seen that calibration of camera parameters, accuracy of locating target characteristics (e.g. point, line or region) and precision of obtaining disparity by stereo matching are main factors influencing the detection accuracy of the above parameters, of which, the precision of stereo matching is particularly critical. About locating obstacles in three-dimensional space based on binocular vision, study of its application in indoor scenes or outdoor structured road scenes is rather extensive, while its application in complicated and unstructured field scene is still at the exploration stage [41][22][31][32]. Meanwhile, the related research work is mainly about the detection of depth distance and contour dimensions, and the detection of azimuth angle is usually omitted. In addition, relevant study results indicate that the absolute value of detection errors tends to increase with the increase of detection distance [41] [42]. In the wide field environment, the effective detection distance is relatively limited. To be specific, detection distance with satisfactory detection accuracy is within 10m and the maximum distance usually does not exceed 30m.

### 4.3. Step three: to obtain motion state of target obstacles

For dynamic obstacles, as described in Section 2.2, in addition to detection of the above static parameters, dynamic parameters such as the magnitude and direction of motion speed are also required to be obtained in real time. The above mentioned obstacle detection methods, no matter based on monocular or binocular vision, and no matter used for locating moving obstacles in images or in three-dimensional space, can only realize the location of all target obstacles at a specific moment but lack correlation of position changes of the same target obstacle at different moments. From the point view of target detection and tracking, all these methods are within the study scope of dynamic obstacles detection. In order to detect dynamic parameters, the same target obstacle should be focused on to determine the change rule of its position in three-dimensional space based on consecutively captured images. Meanwhile, the difference between target measurement value and actual value should be minimized, and the motion state of the target at the next moment should be predicted according to the estimation of its current motion state. On this basis, from the point view of target detection and tracking, detection in this step is within the study scope of dynamic obstacle tracking.

Overall, the current algorithm for target tracking consists of three types. The typical methods of each type and the advantages and disadvantages of these three types are shown in Table 3.

Unfortunately, current study on application of the above tracking algorithms in tracking dynamic obstacles in unstructured field scene is insufficient. In some researches [18], to detect the motion state of target obstacles in field operation scene was mainly based on three-dimensional position coordinates of obstacles at different moments and the corresponding time interval. Specifically, the average motion speed in this period is calculated and directly regarded as the motion speed of obstacles in this period, with the motion direction pointed from the position at previous moment to the position at the current moment. Obviously, when measuring and calculating the speed, such researches may evade the problem of matching target obstacles in different image frames by considering that there is only one target obstacle within the field of view and it is the same target obstacle by default. If
multiple obstacles appear simultaneously within the field of view, matching target obstacles in different image frames will be required before measurement and calculation. In addition, although this measurement and calculation method is simple, it doesn’t take into consideration of measurement errors of the three-dimensional position coordinates caused by interference of noise as well as the final deviation in speed calculation resulting from the measurement errors. In order to eliminate the deviation between the measured and calculated value and the actual value, data processing such as filtering or denoising is required in subsequent work according to change rules of distribution of measured and calculated speed in a continuous time slice.

Table 3 Typical methods used for target tracking and comparison between them

| Main types      | Principles                                                                 | Typical methods                                                                 | Comparison                                                                 |
|-----------------|----------------------------------------------------------------------------|--------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| Generative method | • Establish a model of target appearance in the current frame based on generative models | • Mean shift [43] <br>• Continuously adaptive mean shift [44] <br>• Particle filter [45] <br>• Kalman filter [46][8] <br>• Subspace-based representation [47] <br>• Sparse representation [48] | • Generative models belong to matching models, with heavy computation load and poor real-time capability when obtaining similarity between candidate areas and target template. <br>• Only target itself is considered when forming the model, while background information is ignored. <br>• When appearance of target varies drastically, target is occluded or target information is similar to interference information, processing results may not be that ideal. |
| Discriminative method | • Regard target tracking as a dichotomy problem based on discriminative models<br>• Obtain position information of target objects by using online learning or offline trained classifier to distinguish target objects from background | • SVM-based discriminative method [49] <br>• Boosting-based discriminative method [50] <br>• Method based on online learning detection, e.g. TLD for tracking a single target in a long term [51] <br>• Deep learning-based method [52] <br>• Correlation filtering-based method [53] | • Compared with generative methods, its classifier utilizes background information during training so as to clearly distinguish target objects from background, which brings higher robustness. <br>• Become a mainstream method for target tracking. |
| Hybrid method | • Combine different generative methods [54] <br>• Combine different discriminative methods [55] [9] | • Helpful to increase accuracy, real-time capability or robustness of tracking algorithm by incorporating advantages of different algorithms. | |
knowledge of obstacles, and it is not restricted by the motion of obstacles. In addition, based on binocular parameter calibration and the principle of binocular distance measurement, information of the actual position of obstacles can be simply obtained. However, due to complexity of practical application scenes, especially field operation scene of agricultural machineries, complexity and variance of a number of factors such as types of field operation environment, types, positions and postures of obstacles in the field, light and weather conditions, challenges still exist when using this method to appropriately detect and locate obstacles in images with complicated field background, of which, precise stereo matching of image pairs is the most complicated and time-consuming part.

In addition, limited by complexity of field scene and variance of dynamic obstacles in the field, current tracking algorithms can hardly satisfy the practical application requirements simultaneously in accuracy, real-time capability and robustness required by obstacle avoidance during field operation of agricultural machineries. Although the practical operation scene within the field is relatively simple, to track obstacles in the field with strong robustness and good real-time performance still faces the following challenges: change of forms of target obstacles (e.g. change of postures of pedestrians in the field such as sitting, lying, standing and bending, as well as adjustment of azimuth and attitude of agricultural implements), change of dimensions varying with the change of depth distance, indistinct motion caused by quick movement of target obstacles or by camera trembling with vibration of the camera carrier during operation in the field, target obstacles partially or completely occluded by crops or other static or dynamic obstacles, interference caused by similar background regions (e.g. when tracking targets based on the characteristic of colour, background regions similar in colour to the targets may cause tracking shift), mutual interference between similar target obstacles, change of natural light and real-time capability in practical application. For study in the future, the above object tracking algorithms need to be proactively and boldly used and integrated to discover methods applicable to detecting dynamic target obstacles in field operation scene of agricultural machineries.

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