Review on Applicability of Vision-based Detection Technology in Field Obstacle Detection

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Abstract: In order for robotized field operation by agricultural machineries and complete replacement of manual work in field operation, autonomous obstacle avoidance of agricultural machineries during field operation becomes a critical technology to be solved. For this technology, it is an indispensable requirement and critical premise to timely and accurately perceive static and dynamic information of field obstacles. Firstly, this paper analyzes and determines what obstacles are the target obstacles in the field operation of agricultural machineries from the two aspects - whether the obstacles hinder current operation and whether the obstacles hinder current obstacle avoidance process. Subsequently, this paper mainly discusses the applicability of obstacle detection methods based on monocular vision and binocular stereo vision in field environment: the main existing monocular vision-based methods to detect obstacles are summarized, and their restraints for detecting obstacles in the field are analyzed; considering that precise stereo matching of image pairs is the most complicated and time-consuming part of binocular vision-based detection methods, currently used typical stereo matching algorithms are summarized and compared, and their applicability in field obstacle detection is discussed. At last, the research direction is prospected, and a tendency to detect obstacles for agricultural machineries during field operation is based on multi-sensor fusion system with vision sensor as one of the main sensors.

1. Introduction

Robotized agricultural production is the key for solving the shortage of agricultural labor force, promoting targeted and intellectualized agricultural machineries and improving efficiency and economic benefits of agricultural production. Robotized field operation is an indispensable part of robotized agricultural production, and it is currently at a stage transitioning from the automated to the unmanned (i.e. robotization).

In order for robotized field operation by agricultural machineries and complete replacement of manual work in field operation, the autonomous detection and avoidance of obstacles during field operation of agricultural machineries is one of the most critical technologies to be solved. As a random, real-time and conditional stress behavior, it acts as an important feedback mechanism responding to external safety hazards during field operation of agricultural machineries and is also the critical background for what will be discussed in this paper. In order to achieve it, obviously, the primary task is to timely sense static and dynamic obstacles in the field environment (especially obstacles in the field within coverage of the operation path in front of the machinery) to obtain their overall dimensions, spatial position relative to the current agricultural machinery and their state of motion.
Machine vision technology is an important method for sensing environment information and shows comprehensive advantages such as simple structure, low cost, favorable flexibility, high real-time capability and accurate detection results relative to other environment information sensing technologies (e.g. laser sensing, microwave sensing, infrared sensing, ultrasonic sensing, sonar sensing, etc.), which is feasible and operable to detect the above mentioned field obstacles. In view of this, for the practical application demand of obstacle avoidance by agricultural machineries in field operation, this paper mainly discusses the applicability of vision-based detection technology in field obstacle detection.

2. Target obstacles during field operation

2.1 Types of field obstacles

Substantially, obstacles that agricultural machineries may encounter in field operation can be roughly classified into two types: one is static obstacles, including positive obstacles such as trees/stumps, wire poles, soil mounds, stones, farm tools placed by people and greenhouse, and negative obstacles such as ditches, pits and pools; the other is dynamic obstacles, mainly including humans, animals and other agricultural vehicles in agricultural fields.

2.2 Target obstacles

2.2.1 Direct target obstacles. Generally, target obstacles in field operation of agricultural machineries are located within the current operation zone during each operation moment, as shown in Figure 1, and the area in front of and to be covered by operation of the boom sprayer, surrounded by Line L1, Line L2, and Line L3, is called current operation zone. The width of the current operation zone is equal to the working breadth. While for obstacles located in the area beyond Line L1 (that is, obstacles farther away from the machinery), because they have little effect on local navigation behaviour, they will not be considered. However, obstacles appear in the current operation zone are not necessarily the target obstacles during operation of the machinery in current rows. The following two types of obstacles are the target obstacles that the agricultural machinery must avoid during field operation:

a) Static obstacles (e.g. obstacle No.3 shown in Figure 1);

b) Dynamic obstacles that satisfy the following conditions simultaneously: 1) either direction of longitudinal component of their velocity (that is, velocity component along the operation direction of the current machinery) is identical to the operation direction of the current machinery while the magnitude of their velocity is smaller than speed size of the machinery, or direction of longitudinal component of their velocity is contrary to the operation direction of the current machinery; 2) their distance relative to the current machinery is not far enough and the magnitude of transverse component of their velocity (that is, velocity component perpendicular to the operation direction of the current machinery) is not high enough or even rather low (especially when getting close to 0), which can not ensure that they can transversely and timely leave the current operation zone when the current machinery approaches. For obstacle No.2 and obstacle No.4 shown in Figure 1, when they satisfy the above two conditions, they will be identified as target obstacles.

The above two types of target obstacles are referred as direct target obstacles in this paper, indicating that they are the target obstacles which appear in the current operation zone and may directly hinder operation of the machinery in current rows.

2.2.2 Indirect target obstacles. No matter which obstacle avoidance mode is selected, the agricultural machinery has to make a turn to cross the current operation zone and fully or partially enter the neighboring zone to avoid the obstacles. As there may be obstacles in the neighboring zone which will hinder current operation of turning or detouring to avoid obstacles, once direct target obstacles are detected in the current operation zone, detecting indirect target obstacles (used to indicate target obstacles which are not in the current operation zone but may hinder the current obstacle avoidance
process) in neighboring zones should be initiated to help to plan appropriate obstacle avoidance path to prevent secondary collisions and ensure safety during obstacle avoidance. As shown in Figure 1, if No.2 is a direct target obstacle, No.5 and No.6 are the potential indirect target obstacles.

![Figure 1. Distribution diagram of obstacles during field operation of agricultural machineries](image)

**Notes:**
- **No.1**: boom sprayer (i.e. the current machinery in operation), currently located at the starting headland boundary.
- **A, B**: the projective points of A and B of the farmost nozzles at two ends of the spray boom. Working breadth of the sprayer is determined by the line segment connecting A and B.
- **L1, L2**: representing straight lines passing point A and B respectively, which are both parallel to the operation path.
- **L3**: the straight line perpendicular to the operation path, farther away from the sprayer.
- **Current operation zone**: the area in front of and to be covered by operation of the boom sprayer. Here it is the area surrounded by Line L1, Line L2, Line L3 and starting headland boundary.
- **No.2, No.3, No.4**: representing obstacles of tractor, wire pole and pedestrian in the current operation zone respectively
- **No.5**: obstacle of a wire pole in neighboring zone to the left of the current operation zone
- **No.6**: obstacle of two pedestrians in neighboring zone to the right of the current operation zone

In brief, target obstacles for agricultural machineries during field operation mainly include the above mentioned direct target obstacles and indirect target obstacles. The direct target obstacles are within the current operation zone and may directly hinder the current operation. Detecting indirect target obstacles is required only when direct target obstacles are identified. Indirect target obstacles are generally located in neighboring zones of the current operation zone and may influence planning and implementation of the current obstacle avoidance path.

### 3. Applicability of vision-based detection technology in field obstacle detection

The application of vision sensors in autonomous navigation and obstacle avoidance is being increasingly valued and showing favorable development prospect. Current existing vision-based detection technologies mainly include monocular vision detection technology, binocular vision detection technology and multi-view vision detection technology. Among them, multi-view vision detection technology requires more than 3 cameras, which leads to complicated structure and high cost. Although it may provide more environmental information, it requires a large amount of computation at
the cost of processing efficiency. In reality, it is rarely applied in autonomous navigation and obstacle avoidance system of intelligent agricultural machineries. Therefore, this paper mainly discusses the applicability of obstacle detection methods based on monocular vision and binocular stereo vision in field environment.

3.1 Monocular vision-based obstacle detection

At present, monocular vision-based obstacle detection methods mainly include the following two categories: characteristic-based target detection methods and motion-based target detection methods.

3.1.1 Characteristic-based target detection. In specific scenes (such as structured road) with known types of obstacles (e.g. pedestrians, vehicles, etc.), obstacle regions are extracted from the image background by characteristic analysis based on colours, texture, morphology and edges in monocular images [1][2]; or the obstacles are classified based on pattern recognition methods (e.g. Bayesian Discrimination method) based on characteristics of the obstacle images [3]; or on the basis of learning characteristics of neural network-based or support vector machine-based machine learning or deep learning, the obstacle position detectors or type recognizers are trained with a large number of training image sets to detect the position and recognize the type of the obstacles in the testing image sets [4][5][6]. All above methods are for detecting target objects based on characteristics and are usually applicable to detecting specific obstacles, and these algorithms have difficulties in detecting distant and heavily occluded objects and are, by definition, not capable of detecting unknown object types or unusual scenarios.

3.1.2 Motion-based target detection. For detection of non-specific obstacles in motion, on the basis of monocular images, the following motion-based methods for detecting target objects are mainly used: background difference method [7], inter-frame difference method [8][9], optical flow analysis method [10][11], and motion compensation method [12].

For the above two categories, detailed algorithm classification, main functions and disadvantages of each algorithm, their applicability in unstructured and complicated field environment and main influencing factors are shown in Figure 2.

On the whole, simply using a single monocular vision detection method mentioned above is incompetent for obstacle detection during operation of agricultural machineries in the field due to various types of obstacles, random static and dynamic obstacles, dynamic obstacles moving at random and irregular speed, cameras moving with the agricultural machinery which keeps moving and causes operation background to vary with the geographic position, plus the effect of weather, seasons and light conditions on the operation background.

In addition, monocular vision-based detection technology generally only allows locating obstacle regions in images but can barely stereoscopically sense the surrounding environment. Although the approximate distance can be estimated based on the pinhole camera model [13], only targets with short distance can be approximately estimated and it is hard to obtain accurate azimuth information, while its reliability decreases with the increase of distance. Furthermore, this estimation approach is to assume that the ground is relatively flat and that there are no overhanging obstacles, therefore it is incompetent for detecting obstacles on rugged surface in field scene.
Correcting disparity. According to the varied optimal strategies, current stereo matching algorithms are mainly used for detecting obstacles in images or in three-dimensional space, detection by stereo matching using binocular disparity shows significant advantages. It does not need priori knowledge of obstacles, and it is not restricted by motion of the 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 this method is used 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 view of this, this section focused on the classification, comparison and applicability analysis of various stereo matching algorithms currently used widely at home and abroad.

Establishing a complete stereo matching algorithm usually consists of the following four steps [14]:

- Calculating matching cost, aggregating matching cost, calculating/optimizing disparity and refining or correcting disparity. According to the varied optimal strategies, current stereo matching algorithms mainly consist of local stereo matching algorithm [15], global stereo matching algorithm [16][17] and
The semi-global stereo matching algorithm [18]. Their classification and characteristics are shown in Table 1. The comparison between the above three types of stereo matching algorithms and their adaptability in field obstacle detection are as follows.

Table 1. Comparison of commonly used stereo matching algorithms

| Algorithms | Description | Feature and applicable scene | Improvement methods |
|------------|-------------|------------------------------|---------------------|
| LSM BM     | Matching of each pixel point is transformed into matching of scenes with distinct texture. | Advantages: the algorithm is sophisticated and simple; denser disparity map may be obtained, applicable to scenes with ambiguous texture. Disadvantages: sensitive to lens distortion, image rotation and deformation; strongly influenced by light, contrast, and noise; poor processing effect for regions with occlusion, ambiguous texture, repeated texture and discontinuity; accuracy and efficiency of matching are influenced by size of the matching window; large window matching on overall image, large amount of computation required and poor real-time capability. | The following methods with improved performance are proposed: moving window method [19], multi-window method [20], adaptive window method [21], adaptive weighted window method [22], segmentation-based window method [23], cross-based window method [24], methods for improving robustness to light and at regions with ambiguous texture [25]. A method of obtaining dense disparity map out of sparse matching points based on seed-growth method is proposed [26]. |
| FM         | Matching usually based on the similarity of geometric characteristics of images. Matching element: zero crossing point, inflection point, corner point, boundary outline or segments. Mainly based on the principle of geometric similarity. | Advantages: matching element containing significant statistical characteristics, strong constraint, not influenced by interference of factors such as light and contrast, strong capability of noise immunity and deformation resistance, with small amount of computation and fast speed, able for matching of regions with discontinuous disparity, applicable to scenes with significant geometric characteristics that can be easily extracted in the image. Disadvantages: selection of matching characteristics during pre-processing stage may directly influence accuracy of subsequent stereo matching. Matching based on characteristics of points and lines can only provide sparse disparity map and the processing effect for regions with ambiguous and repeated texture is not favorable. | Methods for solving corresponding points with identical local phase based on theorem of Fourier displacement. |
| PM         | To identify corresponding points with identical local phase based on theorem of Fourier displacement. Matching element: phase information. Based on the theorem of local phase similarity. | Advantages: may effectively restrict effect of high-frequency noise and distortion, less influenced by environment light, may provide dense disparity map of sub pixel level, applicable to parallel processing. Disadvantages: with problems of large amount of computation, phase singularity and wrapping. | Methods for improving the “effect of cross stripes” [29], improving matching results at image boundaries [30], and improving accuracy and efficiency of matching [31] are proposed. |
| GSM DP     | Transform problem of matching into problem of finding the optimal path on corresponding scan lines of left and right image pair. | Advantages: relative to other global stereo matching algorithms, it requires small amount of computation with fast speed, reserves dense characteristics of disparity map, provides global constraints on local regions without texture, and may, to some extent, solve the problem of matching of region with occlusion. Disadvantages: accuracy lower than other global stereo matching algorithms, and the “effect of cross stripes” may occur on the disparity map. | Methods for mitigating the “effect of cross stripes” [29], improving matching results at image boundaries [30], and improving accuracy and efficiency of matching [31] are proposed. |
| GC         | Based on max-flow min-cut theorem, [32], energy function established by stereo matching is used to construct appropriate images to obtain the maximum flow. | Advantages: broad scope of application, applicable to most of complicated scenes, more accurate disparity effect relative to other global algorithms, may provide favorable effect for matching of regions of boundaries and without texture, structure information of original images reserved. Disadvantages: false matching may occur at regions with depth independent of color and boundaries, highly complicated algorithm, low time-efficiency, poor real-time capability, generally combined with other algorithms as appropriate. | Methods for improving the operation efficiency are proposed [35]. |
| BP         | Based on global energy function to set confidence, global energy function minimization is approximately equivalent to maximum probability distribution of Markov random field. | Advantages: high matching accuracy, excellent performance for matching of regions with no texture or ambiguous texture. Disadvantages: poor convergence, high time complexity of algorithm, complicated establishment process of energy function, complicated establishment of MRF model and setting of message transformation mechanism. | Methods for improving the matching effect at regions with occlusion [36], ambiguous texture and repeated constellation [37], methods of hardware design for improving matching efficiency [38], and improved semi-global stereo matching algorithm are proposed [39]. |
| SGM        | Based on mutual information to calculate matching cost, use dynamic programming algorithm as well as smooth constraints to search optimal path and solve disparity. | Advantages: the processing effect for occluded regions and regions with ambiguous texture is still not favorable and its efficiency requires further improvement. | Methods for improving the matching effect at regions with occlusion [36], ambiguous texture and repeated constellation [37], methods of hardware design for improving matching efficiency [38], and improved semi-global stereo matching algorithm are proposed [39]. |
3.2.1 Local stereo matching (LSM). According to matching elements, local stereo matching mainly consists of block-based matching [40], feature-based matching [41] and phase-based matching [42]. Comparison results of the three local matching algorithms are shown in Table 1.

Compared with global and semi-global stereo matching algorithms, local stereo matching algorithms is with light computation load and fast speed (reaching the magnitude of tens of milliseconds [43]). It allows easy hardware implementation and acceleration and can be easily improved. However, due to local optimization, it is sensitive to regions with ambiguous texture, repeated ambiguous texture, discontinuous disparity and occlusion. The false matching ratio of the disparity map is relatively high and its density is relatively low [44][45]. For obstacle detection required by obstacle avoidance during field operation of agricultural machineries, real-time capability is critical, but its requirement for accuracy is not quite strict. Therefore, on the premise of ensuring certain accuracy, matching algorithms with high real-time capability should be given priority, and at the current stage, it is suggested that the local stereo matching algorithms should be preferred, especially feature-based [46] or region-based [47] local stereo matching algorithms or an algorithm combining the two [48].

3.2.2 Global stereo matching algorithm (GSM). In accordance with different optimizing and solving methods for energy function, currently used global stereo matching algorithms mainly include dynamic programming (DP) [31], Graph cut (GC) [49], Belief Propagation (BP) [50]. Contrastive analysis of common global stereo matching algorithms is shown in Table 1. In addition, there are also global stereo matching algorithms based on neural network [51], genetic algorithm [52] and relaxation iteration method [53].

In brief, relative to local stereo matching algorithm, conventional global stereo matching algorithm may provide more accurate disparity value, and the obtained matching results for ambiguous texture and occlusion also exceeds local stereo matching algorithm significantly [54]. Although a denser disparity map is accessible, it requires great computation load with low efficiency (at least a few seconds, usually a dozen of seconds [43][31]) and is not adaptable for hardware implementation and improvement, which limits its direct application in scenes with high requirement for real-time capability such as navigation and obstacle avoidance (e.g. obstacle avoidance during field operation of agricultural machineries). When such method is adopted, acceleration algorithms (such as multi-resolution matching method [44]) or improvement algorithm [55] have to be adopted to increase matching efficiency. Currently, study about its application is still at the applied research stage at low speed or in static detection situations. How to reduce the computation load of global stereo matching algorithm and increase its real-time capability remains to be a key point for current and even future study on global stereo matching algorithm.

3.2.3 Semi-global stereo matching (SGM). Cost aggregation in local stereo algorithm is for windows and it is the difference between elements in the aggregated window, while cost aggregation in semi-global stereo matching algorithm is based on the concept of dynamic planning to aggregate matching cost with different paths. A path with the minimum cost is selected with respect to the overall image. Substantially, semi-global stereo matching algorithm is an improved algorithm based on dynamic planning. It remedies the defect of stripes in the results of stereo matching by using dynamic planning algorithm and improves the shortcoming of low time efficiency of global stereo matching algorithm (as low as a few hundred milliseconds [43][56], usually faster than a few seconds [36]). Relative to local stereo matching method, it provides higher robustness and is not sensitive to light change. It also features high matching accuracy and may form a disparity map with density between maps formed with local and global stereo matching algorithms [57]. It is currently used for navigation and obstacle avoidance in field operation at low speed. However, similarly, the processing effect of such algorithm for occluded zones and zones with ambiguous texture is not favorable and its efficiency requires further improvement.
On the whole, study on stereo matching algorithms used for obstacle avoidance in field operation scene of agricultural machineries mainly face the following challenges: matching under interference factors such as geometric distortion, imaging noise, viewpoint difference and natural light change; matching in situations with discontinuous disparity, obstacles occluded by crops or other static and dynamic obstacles in the field, no texture, ambiguous texture or repeated texture which commonly appear in field scene, characteristics of obstacles similar to field background (e.g. similar color); memory resource consumption in the matching process and real-time capability of the algorithms (to ensure that detected obstacles are at safe distance and avoid the agricultural machineries from being too close to obstacles before the sensors can sense them).

4. Conclusions and future perspectives
Field operation and production are currently at a critical stage transitioning from automation to unmanned technology (i.e. robotization). Obstacles within the field are the main external source of safety hazard in field operation of agricultural machineries. In order for robotized field operation by agricultural machineries and complete replacement of manual work in the field, autonomous obstacle avoidance becomes one of the critical technologies to be solved. And for autonomous obstacle avoidance by agricultural machineries during field operation, it is an indispensable requirement and critical premise for agricultural machineries to timely and accurately perceive static and dynamic information of obstacles in field operation.

Most of the current obstacle detection technologies focus on indoor or simple outdoor scenes with known structure (e.g. structured road environment with favorable conditions), while the study on field operation scene of agricultural machineries is less available. For obstacle detection in complicated and unstructured field environment (with various types of static and dynamic obstacles which appear randomly at random and irregular speed, with their characteristics influenced by distance, occlusion, state of motion and postures, and with geographic differences in operation scenes and uncontrollable environmental factors such as seasons, weather and light), the detection system need to be able to detect farther distance, and have higher environment adaptability, higher accuracy and better real-time capability. Using a single sensing technology (including vision-based technologies described in this paper) to detect obstacle information in outdoor environment may hardly satisfy requirements for real-time capability and reliability at the same time. For this, a variety of sensors may be combined to extend the coverage of the detection both in space and in time, improve the spatial resolution, enhance the robustness of system, increase the reliability of information, reduce the ambiguity of information and ensure higher accuracy and reliability of detection results. Vision sensor is usually taken as one of the main sensors in multi-sensor fusion system, and current typical fusion includes fusion of vision and ultrasonic sensors, fusion of vision and laser radar sensors, fusion of vision and millimeter wave radar sensors, etc. It is a tendency for future outdoor autonomous navigation technologies (especially autonomous navigation and obstacle avoidance in field operation of agricultural machineries) to combine multiple sensors for obstacle detection.

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