# Obstacle Crossing with Stereo Vision for a Quadruped Robot 

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#### Abstract

Autonomous locomotion in unstructured environments is a great challenge for quadruped robots, especially when there is little knowledge about the environments. Based on stereo vision, this paper proposes a locomotion control system for a quadruped robot that is able to perform adaptive locomotion in unknown environments cluttered with many obstacles. To reduce the negative influence of poor light, surface reflection, and textureless conditions, combined with the sum of absolute difference (SAD) method, an efficient post-processing algorithm is investigated to fulfill disparity estimation. According to the calculated terrain maps, a novel gait planning algorithm, which contains different gaits generation and gait transition, is designed to cross over terrains with enough stability and considerable locomotion speed. Experiments on the real robot of traversing complicated surface with stereo vision demonstrate the effectiveness of our system. Video footage can be seen at: http://irdc.ia.ac.cn/robot/.


Index Terms - quadruped robot, obstacle crossing, stereo vision, disparity estimation.

## I. Introduction

Compared to wheeled robots, legged robots have the ability to locomote on different types of surfaces, particularly some unstructured terrains with complicated obstacles. Many kinds of legged robots, especially quadruped robots, such as BigDog [1], SCOUT II [2], SILO4\&6[3], and so on, have been developed for some special uses. Generally, the walking task is established and the knowledge of terrain is known previously. On the other hand, some details of terrains, which would not have fatal effect on walking, are not required. Therefore, the robot can carry out the task successfully without fully sensing the environment. However, considering unknown complicated terrains, there will be greater challenges for autonomous locomotion.

As one of the key sensors for environments' information capturing, the applications are small in number in the field of quadruped robots [4] [5]. The LittleDog, built by Boston Dynamics for the DARPA Learning Locomotion program, is used for the research of machine learning including motion planning and control system. The terrains for experiments are prepared before, and the robot has detailed models of the terrains, leaving the challenging terrain perception task out of

[^0]consideration [6] [7]. Later on, Kolter installs a stereo camera on the LittleDog and conducts some autonomous walking experiments with a terrain modeling algorithm [5]. The main reasons for less research in quadrupeds' autonomous locomotion lie in that attentions are focused on low level control systems and the unknown complicated environments are difficult to model for gait planning. Although autonomous locomotion equipped with stereo vision for quadruped robots has not been studied extensively, it is becoming a trend which will attract more and more attentions to put on it.

In this paper, the assumption is that the unstructured terrains lie on the road with the flat ground plane or the plane's slope changing smoothly. We present a locomotion control system for a quadruped robot that can be used to sense the pavement clattered with large obstacles and plan moving gaits independently using stereo vision attached with it. The emphasis of the system is put on terrain modeling and motion planning. Perception is the first step of terrain modeling and plays a critical role for the following work. Unfortunately, the changeable posture of the quadruped robot itself and the severe environment conditions, such as poor light, surface reflection, and textureless areas of the road and obstacles, bring about difficulties in perception. So in order to get high quality disparity image, a post-processing algorithm combined with SAD for stereo match is proposed to get out of noises [8]-[10]. Then, according to the disparity image and the result of trigonometric calculation, Random Sample Consensus (RANSAC) is adopted to extract the ground plane model for computing the camera's visual angle [11] [12]. Together with attitude angles, the terrain grid maps are modeled accurately based on global coordinate systems. Finally, the cost map of the terrain is constructed and motion planning algorithm, which contains multiple gaits generation and gait transition, is designed. This can improve the walking performance through trotting on flat road segments fast and walking on rugged road segments steadily.

The approach is implemented on the FROG-I (Fourlegged Robot for Optimal Gaits) quadruped robot. FROG-I [13] [14], built in our lab, is attached with stereo vision, as shown in Fig 1. The camera is mounted on the pan/tilt platform. In addition, the locomotion tests in our primary work are limited in straight line of forward and backward directions. Therefore, the head only turns up or down the camera to adjust the line of sight. To get precise terrain model,
the camera, with the resolution of $640 \times 480$, is set to sense the terrain within two meters.


Fig. 1. The FROG-I quadruped robot.
II. Terrain Modeling

Disparity, which is the difference between images from distinct points of view, is the most essential part to obtain terrain's depth and height in terrain modeling. In order to obtain correct disparity values, stereo matching should be adopted to find correspondence between different images. Besides, post-processing filtering algorithm should be designed to increase reliability of disparity map through getting rid of noises and resetting ineffective points. 3D position information based on camera coordinate can be obtained from trigonometric calculation according to the disparity map [10]. Transforming 3D point cloud from camera coordinate to global coordinates and generating grid map are necessary for motion planning.

## A. Stereo Matching

Different from the application based on some prior knowledge, like landmarks, color information, and geometry information, the unseen terrain has no fixed features for identification. To cross over the terrain, any position may be the foothold for adaptive walking regardless of ground regions or obstacle regions. According to the description above, area based stereo matching algorithms are the ideal choices for the perception task. Compared to the area based methods such as the Sum of Square difference (SSD) and the Normalized Cross Correlation (NCC), SAD has the superiorities of less computational time and better match quality [9]. It can be described as

$$
\begin{equation*}
\min _{d=d_{\min }}^{d_{\max }} \sum_{i=-\frac{m}{2}}^{\frac{m}{2}} \sum_{j=-\frac{m}{2}}^{\frac{m}{2}}\left|I_{\text {left }}[x+i][y+j]-I_{r i g h t}[x+i-d][y+j]\right| \tag{1}
\end{equation*}
$$

where, $m$ is the squared window size, $I_{\text {left }}$ and $I_{\text {right }}$ correspond to left and right images, $x$ and $y$ are pixel coordinates, $i$ and $j$ are index variables for the squared window, $d$ is the offset from right image to left image ranging from $d_{\text {min }}$ to $d_{\text {max }}$.

Before stereo matching, normalization to both images
should be done to reduce luminance difference and make texture clear. The matching process is summarized as follows:

1) Selecting a pixel $(x, y)$ in the left image and determining the window size $m$;
2) Comparing the neighborhood to the others in the right image along the some row within the range of $d_{\text {min }}$ to $d_{\text {max }}$;
3) Choosing the best match in the right image for the pixel $(x, y)$ in the left image.

## B. Post-processing

After stereo matching based on SAD method, the initial disparity map comes out. However, the dense disparity map always contains some noises. Furthermore, due to poor light, low texture, and surface reflection conditions, more outliers would appear. Some pixels would be mismatched and others might not be able to find their corresponding points. Fig 2 shows an example of terrain captured while the quadruped robot walking in indoor environment and the disparity map using the above stereo matching method. Surface reflection results in low texture areas, and shadows arise at the boundaries of obstacles. The poor conditions would lead to invalidation of the SAD algorithm for some pixels, and voids would appear in the disparity map. Moreover, mismatched pixels generate inaccurate disparities which scatter in the disparity map. These outliers have a strong negative effect on terrain modeling.


Fig. 2. Up: sample of the left image (left) and the right image (right) captured by on-board camera while walking. Down: the disparity image with outliers.

Researchers have done some work about the disparity processing to get reliable disparity map. Making use of uniqueness constraint, the cross-checking algorithm in [8] [9] is usually utilized to remove outliers. Winner-take-all (WTA) or clustering algorithms are selected to fill in ineffective areas. From analysis of the example in Fig 2, disparity values change slowly along the vertical and horizontal directions except obstacle areas. Several adjacent pixels within a certain distance range have the same disparity value. Considering the processing ability and characteristics of perception in quadruped locomotion, our post-processing algorithm is
designed with two steps.

1) Outlier detection: For each row in the disparity image, there are several different disparity values and mismatched points take up a small part. We count the numbers of different disparity values and put them in sequence. A threshold is set to divide the sequence into two parts. The numbers below the threshold value are sorted out and the corresponding pixels are marked as mismatched disparity values. Then, the positions of the labeled pixels are reset to blank areas.
2) Area filling: Now, the disparity map contains two kinds of areas, effective disparity areas and blank areas. The pixels in blank areas are assigned with the same invalidated value, for example, 255. The invalidated pixels are classified into different types according their positions and replaced by their proximate elements. Eight categories of relationships are displayed in Fig 3.


Fig. 3. Eight types of relations for one invalidated pixel.
Further details are given as described below. In Fig 3, the character $A$ stands for the interested invalidated pixel, $A 1$ and $A 2$ are two other invalidated pixels, and $B, B 1$, and $B 2$ are three pixels with effective disparity values. The relationships in subplot (a) and (b) are prepared for the processing of the invalidated pixel at the beginning of each row. Similarly, (c) and (d) are for the processing of the invalidated pixel at the end, (e), (f), (g), and (h) are for the processing of invalidated pixels in the middle. For each row $i$, the number of invalidated pixels $N_{i}$ should be counted firstly. If $N_{i}$ equal to zero, the processing procedure goes to the next line. Otherwise the relation of every invalidated pixel $A$ with its neighborhood pixels should be classified as $L_{i j}$ and the processing is conducted in accordance with the following rules.

Rule 1: If $L_{i j} \in(a) \cup(c) \cup(e), A$ should be left alone.
Rule 2: If $L_{i j} \in(b) \cup(f), A$ should be replaced by its right pixel.

Rule 3: If $L_{i j} \in(d) \cup(g)$, A should be replaced by its left pixel.

Rule 4: If $L_{i j} \in(h)$, A should be replaced by the average value of its left and right pixels.

## C. Grid Terrain Map Generation

3D information in quadruped body coordinate system changes according to the position of the camera. When walking on uneven ground, the body attitude of a quadruped robot varies continuously as result of the coordinated motion of the four legs. Besides, in order to realize the motion
planning for each leg, it is necessary to convert the world coordinate system to four foot coordinate systems.

The visual angle, which is used to adjust the camera's sensing distance and accuracy, is calculated through extracting the ground plane in camera coordinate system. Because of the complicated ground conditions, it is difficult to get the parameters of the ground plane clattered with many obstacles. In view of this, the RANSAC algorithm is employed to obtain the ground plane equation for visual angle calculation. In camera coordinate system, $N$ 3D points are selected as the sample set for the entire iterative process. First, to calculate the ground plane model, three 3D points should be chosen randomly. With the calculated plane model, distances from all the samples to the ground plane are measured. If the distance of a sample point is less than the threshold value, it can be classified as an effective point, known as an inlier. The above step should be repeated for $m$ times and the numbers of inliers for each step are counted. Finally, the inliers with the maximum number are picked up for the ground plane calculation by using the least square method.

The attitude angles are measured by the gyroscope fixed at the center of the body. With the coordinate transformation, the terrain maps in global coordinate systems are built, however, it can not be employed for motion planning directly. On the one hand, the terrain map is modeled by large volume of data and some data has error with real terrain data as result of the perception and image processing. It is necessary to reduce the redundant data and inhibit the negative effect of the error data. On the other hand, for the reason of camera's spatial resolution, the scene with shorter distances to the camera has high perception accuracy compared to the further scene. More data gathered at the close distance areas and the adjustment of data distribution for the whole scene is necessary for motion planning. Firstly, the grid size is set at $w \times w$ in XY plane of one global coordinate system. $w$ should be chosen according to the visual angle, which corresponds to the perception distance and has an effect on the precision and complexity of grid map. Then, for each grid cell, data elements falling into it are checked and the average value is assigned to the grid cell. For the cell with no data elements, its value is replaced by the neighboring cell in the same row. Finally, the grid map is produced with uniform data distribution.

## III. Motion Planning

To cross over unknown complicated terrain, the motion planner in the control system must evaluate the terrain and present the most suitable footholds for the quadruped robot's low level controller. How to judge the superiority is a crucial issue in motion planning. There are some key factors that should be considered, stability, flexibility, and locomotion speed. In quadruped robots' locomotion, stability is the basic requirement for successful walking without tumbling and sliding. Flexibility can be described as the quadruped robot should pass through the projected foot trajectory waypoints with continuity. The reason of choosing the walking speed as
a factor is that the quadruped robot should not only negotiate the challenging terrain successfully but also as fast as possible.

In order to evaluate the terrain, it is necessary to generate cost map according to terrain's grid map. For the sake of stability while walking, the height of each grid cell and its change rate are taken into consideration. For the grid cell at $i t h$ row and $j$ th column, the cost value is denoted by Cost $_{i j}$ and can be formulated as

$$
\begin{equation*}
\operatorname{Cost}_{i j}=h_{i j}+\operatorname{Dev}\left(h_{i j}\right), \tag{2}
\end{equation*}
$$

where $h_{i j}$ is the height of the cell, $\operatorname{Dev}\left(h_{i j}\right)$ describes the cell's change to elements in $3 \times 3$ neighborhood with the following form,

$$
\begin{align*}
\operatorname{Dev}\left(h_{i j}\right)= & \frac{\left|h_{i j}-h_{(i-1)(j-1)}\right|}{\sqrt{2}}+\frac{\left|h_{i j}-h_{(i-1)(j+1)}\right|}{\sqrt{2}} \\
& +\frac{\left|h_{i j}-h_{(i+1)(j-1)}\right|}{\sqrt{2}}+\frac{\left|h_{i j}-h_{(i+1)(j+1)}\right|}{\sqrt{2}}+\frac{\left|h_{i j}-h_{(i-1) j}\right|}{2},  \tag{3}\\
& +\frac{\left|h_{i j}-h_{i(j-1)}\right|}{2}+\frac{\left|h_{i j}-h_{i(j+1)}\right|}{2}+\frac{\left|h_{i j}-h_{(i+1) j}\right|}{2}
\end{align*}
$$

where $h_{(i-1)(j-1)}, h_{(i-1) j}, h_{(i-1)(j+1)}, h_{i(j-1)}, h_{i(j+1)}, h_{(i+1)(j-1)}$, $h_{(i+1) j}, h_{(i+1)(j+1)}$ stand for the heights of elements in the $3 \times 3$ neighborhood of the cell.

Before planning the motion trajectory, another factor which should be discussed is quadruped robots' walking speed. Generally, to improve the walking efficiency, the measure which is easily conceived is increasing the joint motors' rotating speed. However, for some big quadruped robots, they have large weight because of the materials and load is usually added on them, so the joint motors almost work at full capacity. In our motion planning algorithm, multiple typical gaits and gait transition strategy are employed. Through gaits transforming, the most efficient moving way with both minimum energy consumption and maximal stability is selected. Trot gait, which has higher speed, is adopted to locomote on the road section without obstacles, while in unstructured road conditions, for maintaining the stability, walk gait is utilized. In addition, trot gait and walk gait work in discontinuous manner, that is, the quadruped body is moved forwards while the four legs are all in stance phases. The moving distance of the body in each period is settled. In this way quadruped robots can cross over complicated terrains with both considerable safety and velocity.

Considering the development of motion strategy in anterior and posterior directions, search areas in foot coordinate systems are fixed with X coordinates equaling to zero. The key element in the motion planning algorithm is how to determine the search range to find the suitable footholds. To solve this problem, the planning processes are carried out in each foot coordinate system and the search ranges are determined according the search results of former steps. Then, the quadruped robot has appropriate steps for all of the four legs to move coordinately.

```
Algorithm Motion Planning \(\left({ }^{k} L_{0},{ }^{w} L_{0}, A,{ }^{k} C,{ }^{k} G,{ }^{k} L_{\text {max }}\right.\),
Threshold)
Parameters:
    \(k=R F, R H, L F, L H\)
    \({ }^{k} L_{0}\) : initial foot position at the beginning to foot
    coordinate system
    \({ }^{w} L_{0}\) : initial position of the projection of the center of
    quadruped body to world coordinate system
    \(A\) : body movement during each period
    \({ }^{k} C\) : cost map in foot coordinate system
    \({ }^{k} G\) : grid map in foot coordinate system
    \({ }^{k} L_{\text {max }}\) : maximum planning distance
    Threshold : threshold value for comparison with values
    in cost map
For \(i=1, \cdots, n\)
    For \(k=R F, \cdots, L H\)
        Define \({ }^{k} s_{i},{ }^{k} D_{i},{ }^{k} L_{i},{ }^{w} L_{i}\)
        \({ }^{k} s_{i}\) : stride in the \(i\) th step
        \({ }^{k} D_{i}\) : search area in the \(i\) th step
        \({ }^{k} L_{i}\) : foot position to foot coordinate system after the
        ith step
        \({ }^{w} L_{i}\) : position of the projection of the center of
        quadruped body to world coordinate system after the
        ith step
        \({ }^{k} D_{i}=\left[{ }^{k} L_{i-1},{ }^{w} L_{i-1}+2 A\right]\)
    For \(k=R F, \cdots, L H\)
        If each of the cost values in \({ }^{R F} D_{i},{ }^{R H} D_{i},{ }^{L F} D_{i}\),
        \({ }^{L H} D_{i}\) less than Threshold
            If \({ }^{R F} L_{i-1}-{ }^{w} L_{i-1}<A / 2,{ }^{R H} L_{i-1}-{ }^{w} L_{i-1}<A / 2\),
                \({ }^{L F} L_{i-1}-{ }^{w} L_{i-1}<A / 2,{ }^{L H} L_{i-1}-{ }^{w} L_{i-1}<A / 2\)
                Select trot gait, \({ }^{k} s_{i}=A\)
            Else
                Select walk gait, \({ }^{k} s_{i}=\left(2 A+{ }^{w} L_{i-1}-{ }^{i} L_{i-1}\right) / 2\)
        Else
            Select walk gait
            Assign different weights to cost value according to
            \(\omega=\left(x-{ }^{k} L_{i-1}-\frac{{ }^{w} L_{i-1}+2 A-{ }^{k} L_{i-1}}{2}\right)^{2}+A\),
            \(x \in{ }^{k} D_{i}\)
            Find foothold at minimum cost value in \({ }^{k} D_{i}\)
            Select waypoints in \({ }^{k} s_{i}\) according to the heights in
            grid map
        \({ }^{k} L_{i}={ }^{k} L_{i-1}+{ }^{k} s_{i}\)
    \({ }^{w} L_{i}={ }^{w} L_{i-1}+A\)
        If \({ }^{k} L_{i} \geq{ }^{k} L_{\text {max }}\)
            Return.
```

Fig. 4. Motion planning algorithm for moving in anterior and posterior directions.

The formal description of the motion planning algorithm is given in Fig 4. Search areas are computed for finding optimal footholds. If a cost value in search area is less than the threshold value, it implies that the position is nearly on flat ground plane. When all of the values in search areas for four legs are less than the threshold value, if four feet are in proper positions, then trot gait is selected for the next moving period, otherwise walk gait is chosen with each step equaling to half of the search distance. When obstacles are detected in the walking path, to avoid selecting the foothold at the position
with local minimum value, large weights are assigned to the cost values of the positions at the boundaries of search areas.

According to the strides, waypoints are selected based on the heights in grid map, and then converted from cartesian space into joint space based on the quadruped robot's inverse kinematics. The corresponding joint position values are interpolated using cubic spline interpolation method. In order to prevent discontinuous change between different steps, all of the joint position values are considered as a whole for interpolation. Besides, to maintain the stability while moving with walk gait, a posture adjustment strategy based on potential energy is utilized through changing lengths of legs in diagonal to put the center of gravity (COG) into the support polygon. This part can refer to our related work in [13].

## IV. Experimental Results

## A. Environment Setting and Terrain Modeling Results

The experiments are carried out in indoor environment with smooth floor. The floor, illuminated by fluorescent lamps, is textureless and reflective, as shown in Fig 2. Stone blocks considered as obstacles are selected randomly with the maximum size of about $0.15 m \times 0.15 m \times 0.15 m$. They scatter on the floor and there are shadows around them. The left image is chosen as the reference image for finding corresponding pixels in right image. The disparity estimation method based on SAD and the post-processing algorithm is implemented on the terrain sample. From the comparison with untreated disparity image, the final normalized disparity image, which is displayed in Fig 5(a), is more continuous and credible for terrain modeling.


Fig. 5 (a) The final normalized disparity image. (b) The 3D grid terrain in world coordinate system.

At the moment of perception with onboard stereo vision, through computing with RANSAC algorithm, the visual angle is 59.4 degree. The pitch angle and roll angle measured by the gyroscope are 0.5 degree and 1.1 degree respectively, and the yaw angle is almost 0 degree. Considering the sensing distance and resolution for quadruped robots' autonomous locomotion, the grid size for constructing the grid map is set to $0.01 \mathrm{~m} \times 0.01 \mathrm{~m}$. The 3D grid terrain in world coordinate system is shown in Fig 5(b).

Through analyzing the calculated grid terrain model, we can find that there are some deviations from the real terrain. The first one is that the whole terrain is almost 0.01 m higher than the ground plane. The reasons come from the error of the quadruped robot kinematics modeling and the measurement bias of the body attitude. Another one is the height of ground areas fluctuates in a small range. This is because the stereo vision's perception accuracy changes along with distance and
there is certain approximation while generating grid map. These modeling errors are tolerable while motion planning for autonomous locomotion.

## B. Autonomous Locomotion

In our experiments, the camera's blind area between the quadruped robot itself and the nearest position of the perception terrain can be modeled as flat ground plane, supposing that there is no obstacle in it. In order to locomote more smoothly, the distance of body movement during each period is set to 0.2 m from a lot of experiments. According to the terrain modeling error, the variable of Threshold is set to 0.02 m , that is, any grid cell with the height below 0.02 m can be considered as ground plane area. The initial positions of ${ }^{k} L_{0}$ and ${ }^{w} L_{0}$ can be calculated with the initial joint angles.


Fig. 6 Foot trajectories along vertical line while crossing over the perception terrain. Red solid curve and blue dashed curve stand for RF foot trajectory and LH foot trajectory, and pink dotted curve and black dashdotted curve stand for LF foot trajectory and RH foot trajectory.

Foot trajectories in vertical direction while crossing over the sample terrain are shown in Fig 6. To display the foot trajectories intuitively, the positions are computed in the coordinate systems fixed at hip joints. As labeled in Fig 6, Walk_RF illustrates that the RF leg strides over obstacles in that period, which is similar to Walk_LF, Walk_RH, and Walk_LH. Trot gait and walk gait are crosswise planned based on the terrain conditions. When any of the legs move in the local area which is not even, walk gait is programmed to reduce the locomotion speed and ensure the stability. The moving sequence in a walk period is RF-LH-RH-LF. On the contrary, when all of the four legs have free spaces for choosing footholds, tort gait is programmed to increase the locomotion speed. In addition, because of the global interpolation for the entire moving process, foot trajectories are smooth even during gait transitions.

Fig 7 shows the snapshots of obstacle crossing with stereo vision in ground plane clattered with unknown unstructured obstacles for FROG-I. The first two subpictures and the last two subpictures display the trotting on flat ground areas before and after crossing over obstacles respectively. Subpicture 3, 4, 7, and 8 denote the crossing of walk gaits in obstacle area. Number 5 and number 6 subpictures describe the trotting while the obstacle area locating between front and hind legs. Each subpicture shows the moving legs in swing phase. The video clip is attached with this paper and it is also available on the website of [15].

One point in the locomotion that needs to be noticed is the
slippage factor, especially at the moments of striding over obstacles with larger moving steps. In order to generating larger step, the legs should bend heavily compared to normal state. This would not only increase tangential force but also decrease maximum static friction force between the foot and supporting surface. When the tangential force is greater than the maximum static friction force, slippage would happen inevitably. An effective measure to solve the problem is to replace the material fixed at the end of the foot with others which have larger friction coefficient.


Fig. 7. Snapshots of autonomous locomotion on complicated terrain.

## V. Conclusions and Future Work

In this paper, we proposed a motion control system for quadruped robots' autonomous locomotion in ground plane clattered with many obstacles based on stereo vision. Firstly, a post-processing algorithm together with SAD was designed for disparity extraction during perception. This disparity estimation method can generate effective dense disparity map under severe conditions with low texture, poor light, and surface reflection. The RANSAC algorithm was used to calculate the visual light angle. In addition to the quadruped body's attitude, the terrain grid map was modeled in global coordinate systems according to the robot's kinematics model. The particularly significant element was the motion planning
algorithm, used for programming the footholds for adaptive locomotion. To improve the moving performance, the multiple gaits and gait transition were considered in the motion planning. Trot gait and walk gait were flexibly selected to get high locomotion speed and enough stability. Cubic spline interpolation was used to produce continuous joint trajectories. Our system was applied to FROG-I robot, and the experimental results proved the method's validity.

For the autonomous locomotion with stereo vision, future work will focus on concurrent mapping and localization for adaptive moving in larger space. Moreover, some attentions should be paid to deal with dynamic environments, such as ground planes with moving obstacles. These are of great benefits to practical applications for quadruped robots.

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