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Vision-Guided Walking in a Structured Indoor Scenario

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Original scientific paper

Locomotion of a biped robot in a scenario with obstacles requires a high degree of coordination between perception and walking. This article presents key ideas of a vision-based strategy for guidance of walking robots in structured scenarios. Computer vision techniques are employed for reactive adaptation of step sequences allowing a robot to step over or upon or walk around obstacles. Highly accurate feedback information is achieved by a combination of line-based scene analysis and real-time feature tracking. The proposed vision-based approach was evaluated by experiments with a real humanoid robot.

Key words: biped walking robots, humanoid robots, computer vision, structured environment, real-time feature tracking

1 INTRODUCTION

In comparison to wheeled robots, humanoid robots can move more freely in indoor and outdoor environments. They can climb stairs or step over obstacles. In recent years, significant progress has been made in the design and control of biped walking robots. Considering the mechanical construction and locomotion capabilities of modern humanoids, it seems likely that they will soon be used in everyday life. However, to enable a robot to reach a required level of autonomy, highly developed environment perception together with close coordination between perception and locomotion are necessary. Although being a precondition for any potential practical application of walking robots, the coordination between visual perception and robot walking has been investigated by a relatively small number of research teams. Results from experimental perception-guided robot walking in scenarios with obstacles have been reported in [1, 2, 3, 4].

Our research focuses on the close interaction between visual perception and biped walking [5]. To support our studies we developed a stand-alone vision-based guidance system for walking robots. Information about obstacles on the walking trail is provided by an image processing system consisting of a line-based *scene analysis* module and a *real-time feature tracking* module. This information enables a predictive *step sequence planner* to determine the parameters of adequate step sequences for guiding the robot securely over or around obstacles to a predefined goal position.

Different approaches to image processing for walking robots have been reported including correlation-based stereo vision [2] or model-based stair recognition [6, 7]. The approach based on stereo vision is more general then the model-based approaches and it has already been successfully applied for guidance of walking robots in scenarios with obstacles, where the robots avoided the obstacles by planning the path around them [2, 3]. By stepping over obstacles or climbing stairs, however, a rather accurate positioning of the robot's feet is required, especially if the limited mechanical abilities of today's humanoid robots are considered. This puts high demands on accuracy of image processing algorithms, where the disturbing motion effects which occur during walking, including the vibrations caused by collisions between the robot's feet and the ground, pose an additional challenge. In the approach proposed herein, high accuracy of the obstacle information is achieved by a combination of line-based scene analysis and real-time feature tracking.

Line-based vision systems for biped robots have been reported in [1] and [4]. The vision-based obstacle avoidance strategy presented in [4] considers the situations in which an elongated rectangular obstacle is positioned across the walking trail of the robot, while the scene analysis system presented in [1] is capable of detecting rectangular obstacles of arbitrary dimensions and poses relative to the robot. The scene analysis system discussed in this article represents an improved version of the one proposed in [1] capable of handling a wider range of obstacle situations.

We validated our vision-based guidance approach by performing experiments with the humanoid biped robot Johnnie, developed at the Institute for Applied Mechanics of the Technische Universität München, Germany [8]. The results of the experiments with the robot Johnnie reported in this article are considered to represent a valuable contribution to the numerous theoretical and practical challenges in the field of autonomous vision-guided biped walking.

The article is organized as follows: In Section 2 the concept of vision-based guidance system is explained. The vision-based strategy for detection, classification and localization of obstacles on the walking trail is discussed in Section 3. Experimental results are presented in Section 4.

2 CONCEPT OF VISION-BASED GUIDANCE

For performing a given locomotion task, the guidance system must provide the stabilized biped with the parameters of appropriate step sequences allowing the robot to reach a goal position, while taking into account obstacles on the walking trail. To select appropriate steps for overcoming obstacles, the reactive *step sequence planner* needs sufficiently accurate information about obstacle locations relative to the robot as well as obstacle dimensions.

In the guidance strategy described in this article, obstacle information is supplied by visual feedback. The architecture of the developed vision-based guidance system is shown in Figure 1.

The environment in front of the robot is perceived by a camera system mounted on a pan-tilt head. A stream of camera images represents the input to an image processing system consisting of

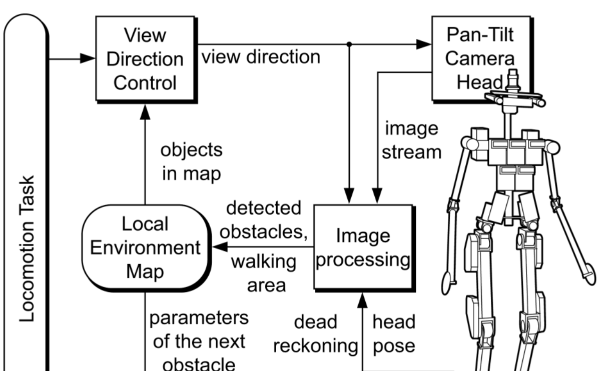

Fig. 1 Architecture of the vision-based guidance system of the biped robot Johnnie

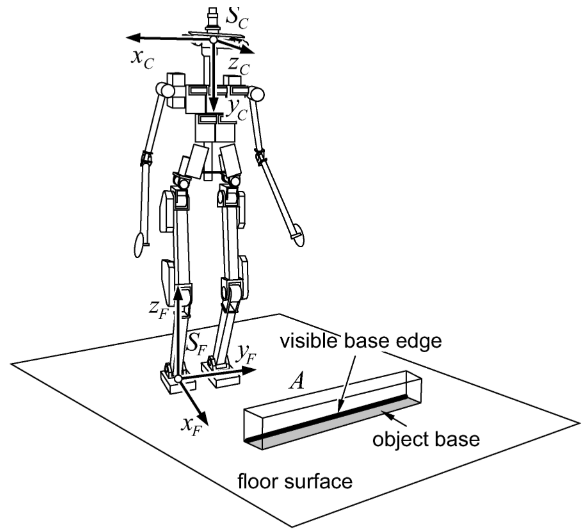

Fig. 2 Vision-guided biped robot with relevant reference frames and an obstacle on the walking trail

the *scene analysis module* and the *dynamic image processing module*. Scene analysis is performed once per step. It includes detection of the boundary of the walking area as well as detection and classification of obstacles lying on the walking trail.

The pose of the obstacles relative to the robot is determined by the pose of their visible base edges relative to the *foot reference frame* S_F presented in Figure 2. The *base edges* of an obstacle are the edges on the boundary of the contact surface between the obstacle and the floor surface. This contact surface is referred to herein as the *base* of the obstacle. The *base* of the obstacle A shown in Figure 2 is represented by a gray region and a visible base edge by a bold line.

The reference frame suitable for the representation of the robot's environment, referred to as foot reference frame S_F, is centered in the sole of the currently standing foot with the z-axis antiparallel to the gravity axis and the x-axis pointing in the walking direction, as shown in Figure 2. This choice has several advantages. First, the currently standing foot is considered to rest on the ground during the execution of a step, thus it is the only part of the robot which does not move relative to the environment. It is assumed that there is no slipping of the robot's foot. By representing the positions of all environment features relative to the foot reference frame, the coordinates of the features remain constant during the step execution. This enables program modules executed at different time instants to use the same environment data. Second, since the origin of S_F lies on the floor surface and its z-axis is parallel to the gravity axis, the z-coordinate of a point represented with respect to S_F is the height of the point relative to the floor surface.

The reliability and accuracy of the object pose estimation is clearly improved by the real-time feature tracking module. This module performs real-time tracking of relevant object features, e.g. the visible edges of object bases, and estimation of their pose relative to S_F. The base edges of the closest obstacles are selected from the set of all edges detected in an image by the scene analysis module. The scene analysis and the accurate obstacle localization are performed using the pose of the camera reference frame S_C relative to the foot reference frame S_F. The transformation ${}^FT_C$ between these two coordinate systems is computed using a kinematic model of the robot, data from the encoders in the robot joints and an onboard inclination sensor [9].

The information about objects detected in the cameras' field of view is used for updating the *local environment map*. This map represents the set of all obstacles appearing on the walking trail during the experiment and the boundary of the walking area detected in the most recent image. All objects in the local environment map are described by their type, size and pose relative to S_F. Since the foot reference frame is always centered in the currently standing foot, it changes its pose relative to the environment after the execution of each step. After the foot reference frame moves to the center of the new standing foot, the parameters of all objects in the map must be transformed from the old foot reference frame to the current foot reference frame. This transformation is computed using the information provided by the robot's dead-reckoning system.

Since the cameras' field of view is limited, the camera system must be directed in such a way that the currently most relevant objects on the walking trail are visible. This is achieved by the intelligent *view direction control* which selects the pan and tilt angle of the camera system corresponding to the view direction which provides the maximum visual information content for the currently relevant locomotion task [5].

The information about the pose and size of the next obstacle on the walking trail is provided as input to the step sequence planner [10]. Since uncertainty in visual estimation decreases as the robot approaches an obstacle, the step sequence is replanned in each step using current visual information. The information about the robot pose relative to the boundary of the walking area is used to correct the walking direction and to keep the robot on the desired path. The set of parameters for the next step to be executed is sent to the *robot locomotion controller* which generates appropriate trajectories for the robot joints and assures their execution.

3 IMAGE PROCESSING

The discussed image processing strategy is presented in Figure 3. It is based on straight line segments extracted from a single camera image and the information about the pose of the camera system relative to the floor surface computed from the robot sensor data. The scene analysis module uses Canny edge detector [11] to extract contours of image points corresponding to the local maxima of intensity gradient. These contours are then segmented into subsets of approximately collinear image points using a split-and-merge procedure similar to the one described in [12]. Each of these point sets is represented by a straight 2D line segment indicating a straight 3D object edge in the camera field of view. The interpretation of this image information is performed based on a set of assumptions about the structure of the robot's environment and lighting conditions. A simple algorithm is applied to determine the base edges of obstacles on the walking trail and the edges representing the boundary of the walking area. The obstacle base edges detected by the scene analysis module are then tracked in realtime and their accurate position relative to S_F is determined by computing the average of a sequence of measurements.

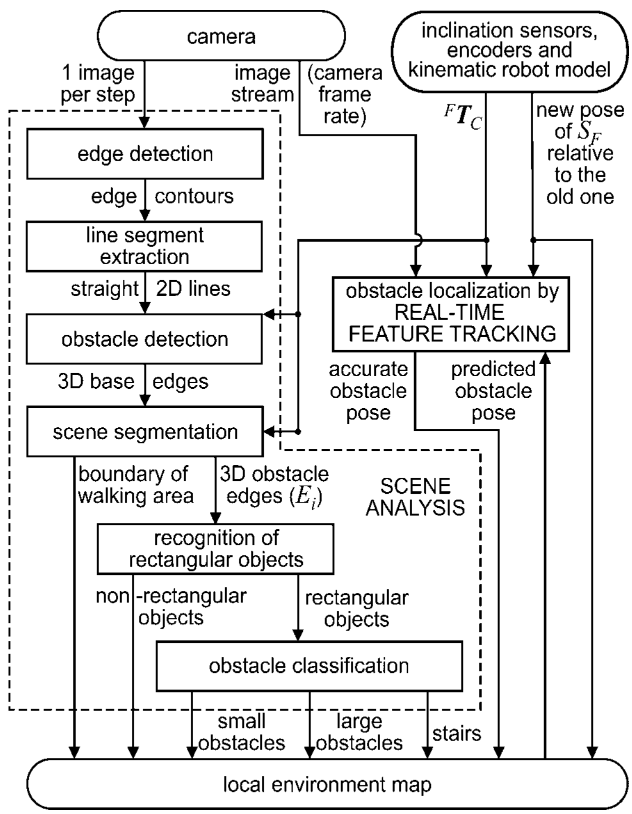

Fig. 3 Image processing strategy

A. Obstacle Detection

The obstacle detection approach applied in the discussed image processing strategy is based on the following assumptions.

1) The robot walks on a flat horizontal floor surface inside a polygonal walking area bounded by a black border, as shown in Figure 4. The floor surface is uniformly colored, non-transparent and non-reflective.
2) The shape of every object positioned inside the walking area is such that the base of the object contains the projections of all object points onto the floor surface.
3) The scenario is lighted by a set of light sources uniformly distributed above the scenario producing very week shadows.
4) The object surfaces are such that the contrast between the object and the floor surface is strong enough for the object base edges to be distinguished from shadows and other artifacts using a simple thresholding technique.
5) The view direction control ensures that the visible base edges of the closest obstacle on the robot's walking trail are contained inside the field of view.

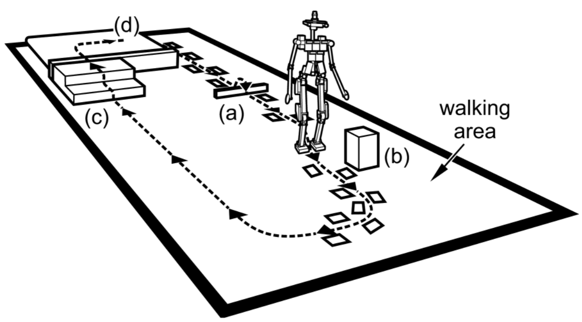

Fig. 4 A typical walking scenario considered in this work. Three obstacles are positioned on the intended walking trail: a barrier (a), a box (b) and a staircase (c). The locomotion task is completed when the robot reaches the goal position (d)

A sample camera image acquired by the camera system mounted on the robot Johnnie is shown in Figure 5.a. The straight line segments extracted from this image are shown in Figure 5.b. The boundary of the walking area and the base edges of the closest objects are detected by determining the set of line segments closest to the bottom of the image. Such a line set is denoted in Figure 5.c by bold lines. The contour *B* obtained by connecting these line segments divides the image into two regions *C* and *D*, as shown in Figure 5.d. Image region *C* above the contour *B* corresponds to the part of the scene partially occupied by objects and the region outside the walking area. Image region *D* below the contour *B* represents the image projection of an obstacle-free region inside the walking area in which the robot can walk safely without colliding with obstacles. This free region can be reconstructed in 3D by projecting the image region *D* onto the floor surface using the method explained in the following.

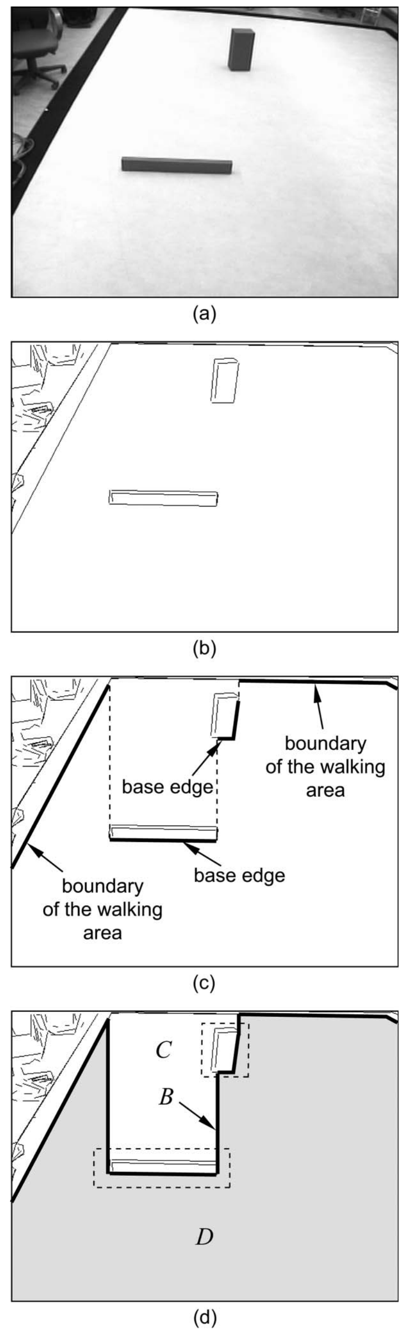

Fig. 5 (a) Camera image. (b) Line segments extracted from the image. (c) Line segments closest to the bottom of the image are denoted by bold lines. (d) Contour B which divides the image into two regions C and D

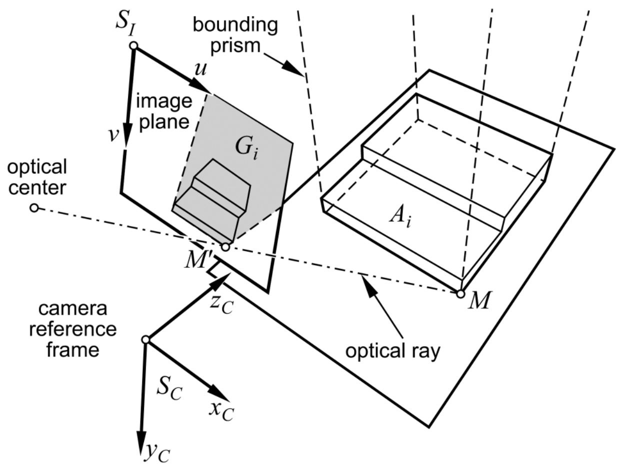

Fig. 6 Projection of a 3D object onto a camera image

Let ${}_C\boldsymbol{x}_M = [{}_Cx_M \;\; {}_Cy_M \;\; {}_Cz_M]^T$ be the coordinates of a 3D point M with respect to the *camera reference frame* S_C, and let $m_M = [u_M \;\; v_M]^T$ be the coordinates of the image projection of M onto the image plane represented with respect to the image reference frame S_I, cf. Figure 6. The relation between ${}_C\boldsymbol{x}_M$ and m_M is given by

$$s\left[\boldsymbol{m}_M \quad 1\right]^T = P\left[{}_C\boldsymbol{x}_M \quad 1\right]^T, \tag{1}$$

where $P \in {}^{3\times 4}$ is the perspective projection matrix of the camera obtained by camera calibration and s is a scaling factor defining the position of the point M on the optical ray.

In order to facilitate the obstacle classification and robot motion planning it is suitable to represent all points in the robot's environment with respect to the *foot reference frame* S_F, as explained in Section 2. Transformation of the point coordinates represented with respect to the camera reference frame S_C to the foot reference frame S_F can be described by

$$\left[{}_F\boldsymbol{x}_M \quad 1\right]^T = {}^F\boldsymbol{T}_C\left[{}_C\boldsymbol{x}_M \quad 1\right]^T, \tag{2}$$

where ${}^F\boldsymbol{T}_C$ is the homogenous transformation matrix and ${}_F\boldsymbol{x}_M$ represents the coordinates of a 3D point M with respect to S_F.

Assuming that the point M lies on the floor surface, the following equation holds

$${}_F\boldsymbol{g}^T \; {}_F\boldsymbol{x}_M = 0, \tag{3}$$

where ${}_F\boldsymbol{g} = [0 \;\; 0 \;\; -1]^{\mathrm{T}}$ is the unit vector representing the orientation of the gravity axis relative to S_F. Since all image points $m \in D$ are assumed to be the image projections of 3D points lying on the floor surface, the 3D coordinates of these points with respect to S_F can be computed using (1), (2) and (3). This way, a free region in front of the robot is determined, whose boundary includes the base edges of the closest obstacles and the boundary of the walking area.

B. Scene Segmentation

The described obstacle detection approach can be used to avoid obstacles by walking around them. However, in order to exploit the abilities of a walking robot to step over or upon obstacles, a suitable obstacle classification strategy is needed. The scene analysis strategy applied in the discussed vision system is to detect the boundary of the walking area and separate obstacles appearing in the walking scenario, and then to analyze each obstacle separately.

The set E of straight line segments denoted in Figure 5.c by bold lines contains the image projections of the boundary of the walking area as well as base edges of the obstacles ahead of the robot. Since the robot walks inside the walking area, the boundary of the walking area always extends outside the camera field of view. Therefore, the chains of co-terminating line segments from the set E whose one or both ends touch the boundary of the camera image are considered to represent the image projections of the boundary of the walking area, as denoted in Figure 5.c. The remaining segments from the set E are assumed to represent the image projections of edges of objects positioned on the floor surface inside the walking area. This subset of E is then subdivided into subsets E_i^*, $i = 1, \ldots, n$ each representing a convex chain of co-terminating line segments. Each subset E_i^* is assumed to include the image projections of edges of a separate object A_i.

According to the second assumption given in Section 3-A, an object A_i is completely contained inside a bounding prism whose base is identical to the object base. Hence, the image projections of all object edges are contained inside the image region G_i representing the projection of the bounding prism onto the image plane. An example is shown in Figure 6, where the bounding prism of a staircase is denoted by dashed lines and its image projection by the gray region in the image plane.

The chains of co-terminating line segments detected in the camera image which are not contained in E, but have a common endpoint with one or more segments contained in E_i^* and which are completely contained inside the image region G_i are assumed to be edges of the object A_i. In the current implementation of this strategy, the length of these line chains is limited in order to decrease the computational time needed for scene analysis.

Using the presented scene analysis strategy, groups of line segments are formed, such as these denoted in Figure 5.d by dashed rectangles, each representing a separate obstacle positioned inside the walking scenario. The group of lines representing the edges of an obstacle A_i will be denoted in the following by E_i. Since only a restricted set of line segments selected by the proposed procedure is considered in further processing, the computational complexity of the scene analysis is kept low.

C. Model-Based Obstacle Classification

Each set E_i of straight 2D line segments obtained by the scene segmentation procedure is considered to represent a separate obstacle which is classified according to its geometry into one of the following three classes. The first class consists of obstacles small enough for the robot to step over. The second consists of obstacles which are too large for the robot to step over, and so can only be passed by planning a path around them. The third class consists of stairs with rectangular steps.

The scene analysis module includes a model-based algorithm presented in the following, which is able to recognize rectangular objects and determine their dimensions. For each 2D line segment from E_i two hypotheses are generated. One hypothesis assumes the 2D line to represent an image projection of a *vertical* 3D edge of an object and the other assumes the line to represent a projection of a *horizontal* 3D edge.

Let $\overline{M_i M_j}$ be a 3D edge with endpoints M_i and M_j. If the edge is *vertical*, it is parallel to the gravity axis. In that case, the following equation must be satisfied

$$ {}_F\boldsymbol{x}_{M_j} - {}_F\boldsymbol{x}_{M_i} = \lambda \left\| {}_F\boldsymbol{x}_{M_j} - {}_F\boldsymbol{x}_{M_i} \right\| {}_F\boldsymbol{g}, \quad \lambda \in \{-1,1\}. \tag{4}$$

From (1), (2) and (4) it follows that only the straight line segments with certain orientations in the camera image can be considered as image projections of hypothetical vertical edges [13]. If a 2D line does not have such orientation, the hypothesis that the line represents the image projection of a vertical 3D edge is rejected.

If $\overline{M_i M_j}$ is *horizontal*, then it is perpendicular to to the gravity axis, i.e.

$$ ({}_F\boldsymbol{x}_{M_i} - {}_F\boldsymbol{x}_{M_i})^T {}_F\boldsymbol{g} = 0. \tag{5}$$

Each 2D line detected in the camera image can hypothetically represent a horizontal edge whose orientation with respect to the frame S_F can be determined using (1), (2) and (5).

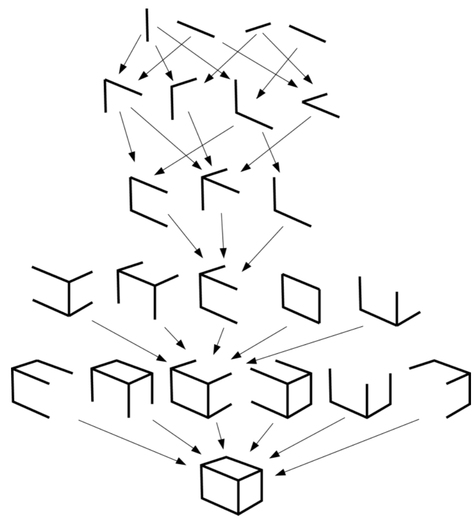

Fig. 7 Hierarchical grouping of edges. First, pairs of mutually orthogonal edges sharing a common endpoint are formed. The edge pairs sharing a common edge are then grouped into more complex structures

The hypothetical 3D edges generated from the set E_i of 2D line segments are grouped using the following procedure. First, pairs of orthogonal co-terminating edges are formed, as shown in Figure 7. The edge pairs sharing a common edge are then grouped in more complex rectangular structures. Assuming that the obstacle is lying on the floor surface, the z-coordinate of its base points with respect to S_F is 0, cf. Figure 2. Hence, the x and y coordinates of a base point M can be obtained using (1), (2) and (3). The coordinates of the other points are determined by using the coordinates of the base points and Eqs. (1), (2), (4) and (5). After the coordinates of all obstacle points are determined, the information of obstacle size is available, which is used for obstacle classification.

The described obstacle reconstruction procedure can be applied only if the shape of an obstacle is rectangular. If the arrangement of the line segments in the set E_i is such that it does not resemble a rectangular object, the obstacle is classified into the second class, i.e. as an obstacle which can be avoided only by going around it.

D. Accurate Obstacle Localization

A critical parameter for correct foot positioning is the distance of from the currently standing foot to the closest obstacle, which therefore has to be estimated with a accuracy of a few centimeters. In our vision system, a high accuracy of the obstacle distance estimation is achieved by averaging over a sequence of distance measurements. Visible base edges of the closest obstacles identified by the scene analysis module are tracked in real-time during a time interval of step execution. Its pose relative to the standing foot of the robot is estimated from each image. The estimation is performed using (1), (2) and (3) applied to a pair of points of the base edge. The real-time feature tracking is described in more detail in [14].

The accuracy of the transformation ${}^{F}\boldsymbol{T}_{C}$ needed for the applied estimation method directly affects the accuracy of the obstacle localization and thus the overall performance of the guidance system. Collisions between the robot's feet and the ground can generate vibrations of the cameras resulting in uncertainty in determining the transformation ${}^{F}\boldsymbol{T}_{C}$ and blurred images. In order to reduce this effect, image acquisition is performed during the phase of the step execution when the camera movement is most steady. The respective interval is defined by the robot's trajectory planning algorithm [8].

4 EXPERIMENTAL RESULTS

To test the suitability and efficiency of the reported vision-based guidance approach the stereo camera head developed at our laboratory was mounted on top of the robot Johnnie. The vision system comprises two cameras with view-angles of 55° in horizontal and 42° in vertical direction and a stereo base-line of 240 mm. Gray-scale (8 bit) images with resolution 640×480 pixels are used.

Figure 4 shows the walking scenario for a typical experiment in which the perception system guided Johnnie to a given goal position (d). The robot was given the task to walk from a starting position following the border of the 4×8 m walking area shown in Figure 4. The walking task terminates after the robot has climbed to the top of a staircase. The ability of the guidance system to adapt the robot locomotion to the environment is tested by positioning different obstacles on the walking trail. In a typical experimental setup shown in Figure 4 two obstacles are considered: a barrier (a) and a box (b). The size of the barrier is such that the robot can stride over it. On the other hand the box is too large for the robot to step over it. Depending on the environmental situation the guidance system decides that a step sequence needs to be planned allowing the robot to pass the box.

During walking, scene analysis was performed once per step on images acquired by the camera system. Obstacle detection and estimation of their size and distance were performed using the data from the encoders in the robot joints and an inclination sensor. The time needed for execution of the scene analysis algorithm on standard PC hardware with a 1.3 GHz processor was less then 0.5 s.

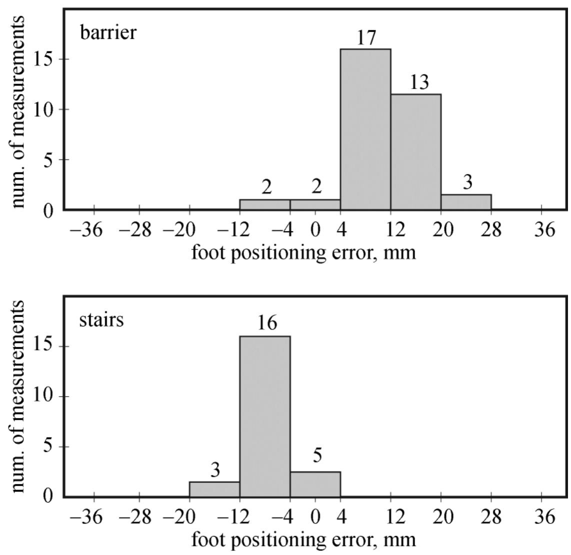

Fig. 8 Histogram of the foot positioning error in front of the barrier and stairs

The object features selected by the scene analysis performed once per step are tracked in real-time by the real-time feature tracking module. An accurate estimate of the obstacle distance relative to the currently standing foot of the robot is computed by averaging over a sequence of measurements obtained during a time interval of step execution when the camera movement is most steady.

Figure 8 shows a histogram of the foot positioning error in front of the barrier and the staircase recorded in a series of experiments.

In the current implementation of the guidance system, the parameters of step $i+1$ are sent to the robot before the execution of the step i starts. Thus, the reference foot position in front of an obstacle is computed using the visual estimation obtained two steps ahead of the obstacle. Hence, the foot positioning error represents the sum of the visual estimation and the dead reckoning error accumulated over two steps. The histograms demonstrate that in all experiments the error was inside the bounds of ±30 mm. The achieved accuracy of the vision system together with the robot control and stabilization system enabled Johnnie to safely step over a 40 mm wide and 80 mm high barrier as well as to reach and climb the stairs.

Figure 9 shows Johnnie stepping over the barrier, walking around the box and climbing the stairs.

The capability of the biped to react to sudden changes in the environment was validated by putting an obstacle in front of the robot during walking. When walking started, there were no obstacles in front of the robot. As a consequence the step

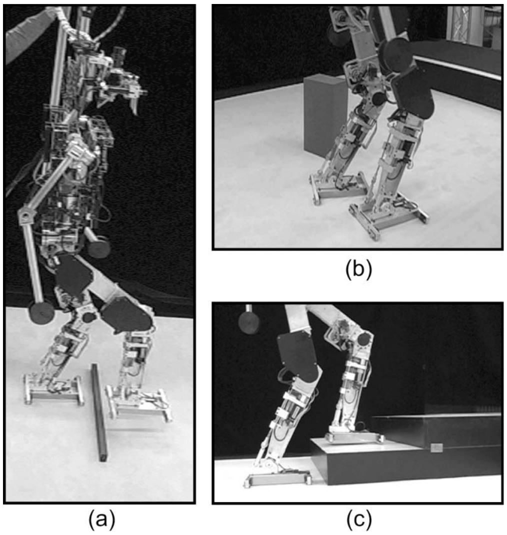

Fig. 9 Johnnie is stepping over a barrier (a) walking around a box (b) and climbing stairs (c)

sequence planner generated a sequence of pre-selected nominal steps. When an obstacle was placed inside the camera system's field of view, the obstacle was detected and its location and dimensions were estimated. The local environment map was updated with the obtained information. Consequently, the old step sequence was replaced by a new one which allowed the robot to successfully cope with the obstacle.

5 CONCLUSIONS

In this article, an approach to vision-guided robot walking is reported. A model-based scene analysis algorithm is applied to provide the information about obstacles on the walking trail. This information is used to initialize the real-time feature tracking process which precisely estimates the obstacle pose. The object recognition and the pose estimation are performed using the information about the camera system orientation obtained by the encoders in the robot joints and an inclination sensor. The obstacle data are used by a predictive step sequence planner to select appropriate steps allowing the robot to overcome the obstacles and reach the goal position.

The presented experiments with the humanoid biped robot Johnnie were conducted to examine the performance of the developed vision-based guidance approach. Since the images were acquired during a time interval of the step execution when camera movement is most steady, obstacle classification and accuracy of visual estimation were not degraded significantly by camera movements caused by walking. The dynamic updating of the local environment map and continuous step sequence planning allowed the robot to react to changes in the environment.

Although the scene analysis system applied in the experiments with Johnnie was limited to handling a restricted class of obstacle situations, its abilities were sufficient for evaluation of basic obstacle avoidance strategies for walking robots. Furthermore, the experience and data gathered during these experiments have provided the basis for the development and evaluation of a more advanced scene reconstruction system presented in [15] and an intelligent gaze control strategy presented in [16].

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Vođenje hodajućeg robota u strukturiranom prostoru zasnovano na računalnome vidu. Lokomocija dvonožnog robota u prostoru s preprekama zahtijeva visoki stupanj koordinacije između percepcije i hodanja. U članku se opisuju ključne postavke strategije vođenja hodajućih robota zasnovane na računalnome vidu. Tehnike računalnoga vida primijenjene za reaktivnu adaptaciju slijeda koraka omogućuju robotu zaobilaženje prepreka, ali i njihovo prekoračivanje te penjanje na njih. Visoka točnost povratne informacije postignuta je kombinacijom analize linijskih segmenata u sceni i praćenjem značajki scene u stvarnome vremenu. Predloženi je sustav vođenja hodajućih robota eksperimentalno provjeren na stvarnome čovjekolikome robotu.

Ključne riječi: dvonožni hodajući roboti, čovjekoliki roboti, računalni vid, strukturirani prostor, praćenje značajki u stvarnome vremenu

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