

# Real-Time 3D Map Building for Local Navigation of a Walking Robot in Unstructured Terrain

B. Gaßmann, L. Frommberger, R. Dillmann  
Forschungszentrum Informatik  
Haid-und-Neu-Str. 12–14  
76131 Karlsruhe, Germany  
gassmann@fzi.de

K. Berns  
Arbeitsgruppe Robotersysteme  
FB Informatik Universität Kaiserslautern  
Gottlieb-Daimler-Straße, Geb. 48  
67653 Kaiserslautern, Germany

**Abstract**—Locomotion of walking machines on a well defined path in unstructured terrain requires a model of the environment. But, in particular, middle sized robots like LAURON III don't provide the possibility to carry large or heavy sensors. This paper focuses on generating a 3D map of unstructured environment on the basis of sparse sensory information. In respect of walking robots this covers at first the selection of the next footsteps. For this purpose the advanced inference grid is introduced as a variant of the vector field histogram for the representation of the environment.

## I. INTRODUCTION

Navigation in unstructured terrain is a difficult challenge. Compared to structured environments, the geometry of unstructured areas cannot be described in detail, because there is no complete a-priori knowledge available on the surface and the ground conditions on which the walking machine has to operate. Legged machines are very suitable for navigating in this sort of terrain due to the great flexibility in their motion and their ability to cope with very uneven environment. Proper navigation of walking machines, however, demands fairly complex control mechanisms, and suitable walking behavior can only be achieved by considering knowledge of the surrounding environment. Therefore, building a world model and analyzing the gathered information is a necessary assumption to modify the robot's behavior in a sensible way. Because a walking machine operates very flexibly and can cope with obstacles in different ways, a 3D model is required to provide an as much detailed environmental knowledge as possible.

Much work concerning 3D environment models has already been done, but it mostly focuses on wheel-driven vehicles (i. e. [1], [2], [3]). All of those use some sort of *occupancy grid* [4] for representation, which proved to be very effective, but none of these approaches considers the specific needs of a walking robot: since legged machines are supposed to overcome obstacles instead of just avoiding them, the placement of the feet is an important goal that must be taken into account when designing the environment model. Some big walking machines like the Adaptive Suspension Vehicle (ASV) [5] select footholds on the basis of an elevation map. But the ASV is equipped

with a battery of more than 100 sensors, which is only possible because of its huge size and cannot be transferred to smaller machines like our test platform LAURON III [6]. Additionally, possible foothold positions are rated merely as acceptable or not acceptable. Particular path planning approaches for walking machines exist as well [7], but they omit both the data acquirement and the foot positioning problem. However, before being able to solve problems like path planning, it is necessary to determine the very next foothold positions of the robot

In this paper a method is introduced to close this gap: it shall enable a small, legged robot with comparably sparse sensory power to gather important information on the surroundings, build maps of the environment and process the gained knowledge in real-time. Suitable foothold positions in the machine's proximity are to be found, enabling the robot to cope with very difficult terrain and overcome obstacles.

In the following first the test platform LAURON III and its basic locomotion control is described. Then our approach for the selection of adequate footholds based on the so-called *advanced inference grid* is introduced. The paper ends with an experimental evaluation of the method.

## II. TEST PLATFORM LAURON III

LAURON III is a stick insect like walking machine built as a universal platform for locomotion in rough terrain [6]. It consists of a main body, a head and six equal legs, each providing three degrees of freedom. With all components mounted on, the weight of LAURON III is about 18 kg. It has a length and width between the footsteps of about 70 cm and a maximal payload of 10 kg. The maximum distance between body and ground is 36 cm, the maximum velocity is given by  $0.3 \text{ ms}^{-1}$ . LAURON III matches the requirements for autonomy, whereas the accumulators last for about 45 min (average power consumption 80 Watt). Its joint angles are measured by optical encoders, the load of the motors could be determined by the measured currents. LAURON III is equipped with foot force sensors mounted on the lower leg, allowing the measurement of all three axial force components. This construction enables the determination of the contact forces including direction

and quantity. The main body carries an inertial sensor box delivering information about the angular velocity and the axial acceleration, each in three dimensions. Furthermore, a laser distance sensors (range: 20–500 cm, resolution: 0.5–3 cm) is fixed in the middle of the head for scanning the near environment. The sensor is fully movable around two axes, allowing the laser to be pointed at every point in the proximity of the machine.

The control of LAURON III [8] is realized by a behavior-based architecture implemented with the modular controller software architecture MCA2<sup>1</sup>. For walking in unstructured environment, different levels of behavior become necessary. There are fast low level behaviors or reflexes like elevator reflex for lifting a leg over an obstacle if a collision occurs or pressing the foot on the ground while a leg supports the robot. Furthermore there are behaviors for generating the general leg movement during support and swing phase, behaviors for coordinating the legs and for controlling the body posture. In future more sophisticated behaviors at a higher level of control may influence the walking strategy for climbing a rock, walking over a gap or generating a plan for walking towards a given goal position. Because the behavior control is directly affected by local terrain conditions, it is necessary to acquire information by exploiting diverse sensors.

### III. ENVIRONMENT MODELING

Knowledge of adequate places for foot positioning enables the robot to perform a controlled and secure walking behavior. To find those we have to build a suitable model of the robot's environment and find representations to extract the needed information.

#### A. DATA ACQUISITION AND REPRESENTATION

Because navigation is supposed to be done in unstructured, mostly unknown terrain, the representation of the environment is subject to some restrictions. It must be possible to start with an empty map because no a-priori knowledge can be assumed. Also our method must be completely independent of edge detection, as no edges can be expected in a natural environment. In order to place the feet at proper positions the resolution of the maps, especially in the direct surroundings of the machine, must be adequately high and as exact as possible. Taking these points into account leads us to the necessity of using a geometric approach for representing the environment.

Small robots are not able to carry big and heavy sensor equipment, so map building must be possible on the basis of sparse sensory information. To handle spots of insufficient environment information, the model must provide the possibility of invoking additional measurements.

Taking all these points into account the use of some kind of *occupancy grid* [4] is very suitable. Our approach,

<sup>1</sup><http://mca2.sourceforge.net/>

the *advanced inference grid*, is a variant of the *vector field histogram* [9]. Out of each measurement (which can be achieved by the distance laser sensor, an infrared sensor or pressure sensors in the robot's feet) the global coordinates of the hit position and the corresponding grid cell are calculated, and its content is modified. For the distances sensor, all the cells lying on a straight line between the detected cell and the one corresponding to the robot's head position, which are obviously empty, are also regarded. In our approach the content of each cell does not consist only of an occupancy value, a *credibility* value is also stored. Both values range from 0 to 1. The occupancy value  $\text{occ}(C)$  reveals the occupancy state of the area represented by the grid cell  $C$ —insofar as it is known. The credibility value  $\text{cred}(C)$  states how much we are able to trust this observation. This division is done by the following purpose: we want to distinguish whether a stored occupancy of i.e. 0.5 indicates a fairly correct observation of an inhomogeneous environment or just measurements of improper quality, a drawback that, if detected, can easily be repaired by invoking additional measurements or, alternatively, a more cautious walking behavior of the robot.

Given a time  $t$  and a new occupancy observation  $\text{obs}_{t+1}(C) \in \{0, 1\}$ , the contents of the corresponding cell  $C$  are updated following this equation:

$$\text{occ}_{t+1}(C) = (1 - k_{in})\text{occ}_t(C) + k_{in}\text{obs}_{t+1}(C) \quad (1)$$

$$\text{cred}_{t+1}(C) = (1 - k_{in})\text{cred}_t(C) + k_{in}k_{cred} \quad (2)$$

Here  $k_{in} \in [0, 1]$  denotes how strongly the current observation  $\text{obs}_{t+1}(C)$  shall influence the cell contents,  $k_{cred} \in [0, 1]$  states the credibility of the current measurement.  $k_{cred}$  is dependent on the quality of the sensor delivering this measurement (which is expert knowledge), the motion status of the robot (an inert machine provides better results) and the neighborhood homogeneity of the determined cell. It is unlikely to find a single occupied cell in an otherwise empty environment, so measurements indicating homogeneous regions are more likely to be credible. Given an observation  $\text{obs}(C)$  and a set of cells  $\mathcal{N}$  in the neighborhood of  $C$ . Then  $n(C, \text{obs}(C))$  is a measure for the neighborhood homogeneity:

$$n(C, \text{obs}(C)) = \frac{\sum_{D \in \mathcal{N}} |d(C, D)(\text{obs}(C) - \text{occ}(D)\text{cred}(D))|}{|\mathcal{N}|} \quad (3)$$

$d(C, D)$  is a distance measure between  $C$  and  $D$ . For this work only directly neighboring cells are regarded and  $d(C, D) \equiv 1$  is used. Finally, the quantity of prior measurements also affects  $k_{cred}$ —we don't want to trust the very first measurements at a point too much.

The overall influence parameter  $k_{in}$  depends on both  $k_{cred}$  and on qualitative information on the acquirement of prior measurements having flowed into the contents

of the corresponding cell. These values (age of last measurements, number of prior measurements and number of different contributing sensors) are called *meta information* and are also stored in  $C$ . Figure 1 shows the data flow while calculating  $k_{in}$  and  $k_{cred}$ .

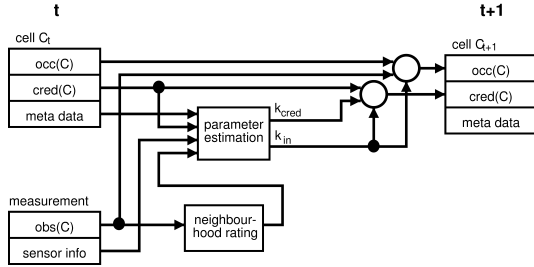


Fig. 1. Schematic illustration of data flow and interaction while calculating  $k_{in}$  and  $k_{cred}$ . A cell  $C_t$  and a new incoming measurement  $obs(C)$  concerning this cell at a time  $t$  result in a cell  $C_{t+1}$  with modified content. Neighborhood rating follows equation (3), parameter estimation is done by fuzzy reasoning.

The use of this meta information is one of the main differences from the vector field histogram: the influence of each measurement is dependent on the quality of both prior and actual data. Overaged information will be easily erased out of the model, new and good observations will have greater influence than redundant weak-quality information.

The calculation of both parameters  $k_{in}$  and  $k_{cred}$  is done with the help of fuzzy logic, based on a set of easily adaptable rules like for example

IF neighbourhood = medium THEN  $k_{cred}$  = high  
 IF sensor quality = high THEN  $k_{in}$  = high  
 IF age = outdated AND amount of measurements = many THEN  $k_{in}$  = very high

As an example, figure 2 shows the results of the fuzzy parameter calculation in relation to age and quantity of prior measurements.

The use of fuzzy reasoning for cell updating has many advantages: non-linear correlations are easily couched in terms, external model knowledge can be written down in a straightforward manner, the rules are easily extensible by just adding new ones, and they are simple to understand and adapt. All of this offers excellent portability to other robot architectures, which was one of the main goals of this work. Finally, the method proved to be very efficient under real time conditions, offering better results with fewer measurements compared to the vector field histogram approach.

### B. BUILDING MAPS OF THE ENVIRONMENT

Holding three dimensional data results in a need for a huge amount of memory, even though we use octrees and quadtrees for representing the maps' contents. In order to

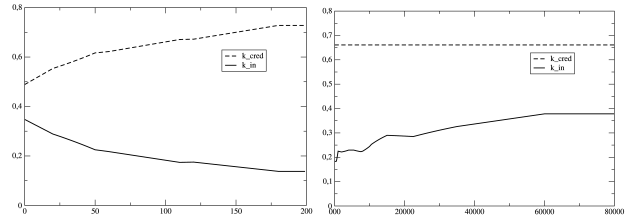


Fig. 2. Influence and credibility parameter  $k_{in}$  (solid line) and  $k_{cred}$  (dashed line) in relation to the amount (left) and the age (in ms, right) of prior measurements. All other incoming values are set fixed. The more data has been acquired for a cell previously, the lower is the influence of the new measurement and the higher is its credibility. Also influence is lower if the last measurements concerning this cell are new. Credibility does not depend on the age of previous measurements.

save memory and gain processing efficiency, several maps with different size and resolution are stored. The three dimensional base map contains the immediate surrounding (about 4 m in each direction) of the robot and scrolls as the machine is moving. Based on the base map, other, global maps for further processing are generated. In particular, small 2D maps are generated in the surrounding of the expected target locations of the robot's feet every time a new step is to be made.

Based on the size of LAURON III's feet we use a grid resolution of  $5 \times 5$  cm in the plane and 1 cm in height for the base map. The foot environment maps also use a grid size of  $5 \times 5$  cm.

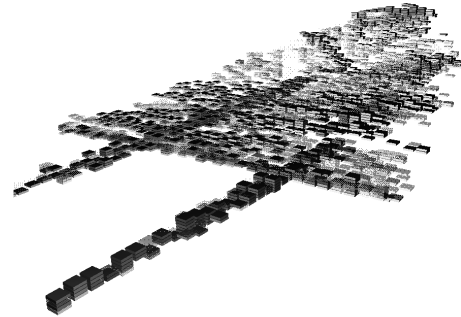


Fig. 3. Visualization of the 3D environment map. Unclassified areas are white. The two linear traces have been acquired by the foot sensors only, since the distance sensors only scan in front of the robot. Darker cells (as seen especially on the trace of the robot's feet) indicate higher credibility. On the screen display credibility is represented by color.

Local foot environment maps are principally generated by doing a projection to the  $xy$ -plane (see algorithm 1<sup>2</sup>). Since the aim of these maps is to find a position to place the robot's foot on, we look for the highest elevation for each coordinate in the plane. Among all the cells of a base map  $U$  on a given position  $(x,y)$  in the  $xy$ -plane that surpass a minimal occupancy  $occ_{min}$  we take the cell  $U(x,y,z)$  with the maximum  $z$ -coordinate (as long as it is

<sup>2</sup>In the algorithms statements in curly braces are comments.

inside the range the machine is capable of overcoming) and store this elevation value in a 2D map in cell  $L(x, y)$ , including the credibility value for the detected cell. In a sense, two different maps are generated: an elevation map and a credibility map. As foot environment maps have a small constant size (which indeed can be adapted while the system is running), the generation process is done in  $O(\log n)$  because of the reporting complexity of the octree.  $n$  here denotes the size of the base map in each dimension. For the experiments shown in this paper map sizes between  $25 \times 25$  and  $50 \times 35$  cm have been used, so the maps contained between 25 and 70 cells.

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**Algorithm 1** Generation of a foot environment map  $L$  around a position  $P_v$  out of a base map  $U$

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generate empty grid map  $L_{P_v}$  centered around  $P_v = (x_v, y_v)$ 
for all  $(x, y) \mid L(x, y) \in L_{P_v}$  do
   $L_{x,y}^* = \{(x, y, z) \mid \text{occ}(U(x, y, z)) \geq \text{occ}_{\min} \wedge U(x, y, z) \in U\}$ 
  if  $L_{x,y}^* = \emptyset$  then {no proper position for foot placement found}
     $h(L(x, y)) = \text{undefined}$  {height information}
     $\text{cred}(L(x, y)) = 0$ 
  else
     $z^* = \text{argmax}_z \{(x, y, z) \in L_{x,y}^*\}$ 
     $h(L(x, y)) = z^*$  {height information}
     $\text{cred}(L(x, y)) = \text{cred}(U(x, y, z^*))$  {credibility according to 3D cell}
  end if
end for

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In the same way a 2D map of bigger range of several meters is generated. In addition to occupancy and credibility information other environmental attributes detected by the system (i.e. ground softness or emergence of navigation problems) can be stored. The creation of such maps has a complexity of  $O(k \log n)$  where  $k$  denotes the number of occupied cells in the base map. Since  $k$  becomes  $n^3$  in the very worst case, the creation of these maps under real time conditions (which is not needed, though) can not be assured and should be done in a background process.

Merging some of these maps can generate even bigger maps (with smaller resolution) by putting together the contents of adjacent cells. This procedure can be carried on to generate a global map of all discovered environments. At this point, however, our work focuses on exploring the local surroundings.

### C. FINDING PROPER FOOT POSITIONS

Every time before the execution of a new step is invoked, a new local foot map  $L$  is generated out of base map  $U$  around a position  $P_v$  (algorithm 1), which is the expected next foot position under the assumption that the ground would be completely flat and therefore the normal walking behavior does not need to be modified. The next step is to check the overall quality of  $L$ . A map's quality  $\text{cred}(L)$  can be regarded as sufficient if both the average credibility of all cells and more than half of the single

cells surpass a threshold  $\text{cred}_{\min}$ . Following this thought,  $\text{cred}(L)$  is defined as

$$\text{cred}(L) = \min \left( \frac{\sum_{x,y} \text{cred}(L(x,y))}{|L|}, \text{median}(\text{cred}(L(x,y))) \right) \quad (4)$$

If  $\text{cred}(L) \leq c_{\min}$ , additional sensor measurements for this area are invoked. For this purpose the scan strategy of the laser equipped head is temporarily changed: instead of scanning long lines in front of the robot's body, the laser is pointed to the area acquired by the local map for additional scanings to increase the map's credibility. After finishing, the scan strategy reverts to normal and a new local foot environment map  $L$  is generated.

The best foot position  $P_p$  is calculated out of  $L$  around position  $P_v = (x_v, y_v)$  by

$$P_p = \underset{x,y}{\text{argmax}} \left( \text{cred}(L(x,y)) (1 - k_L(x,y) \| (x_v, y_v) - (x, y) \|) \right) \quad (5)$$

where  $\|$  denotes the Euclidean norm. This determines the most credible position given in the local map, which can be expected to be a secure place for the robot's foot. The parameter  $k_L$  ensures that positions  $(x, y)$  in the center of the map (which are close to the machine's "normal" walking behavior) are more likely to be chosen. If  $k_L$  is defined i.e. as

$$k_L(x, y) = \left( \frac{\| (x_v, y_v) - (x, y) \|}{\max_{(p,q) \in L} \| (x_v, y_v) - (p, q) \|} + 1 \right)^{-1} \quad (6)$$

cells at the border of the map need twice as high credibility values to be chosen than those in the center. Finally, the walking parameters for moving the foot to  $P_p$  are calculated and sent back to the walking control module. This enables the machine to perform planned steps on elevations or into slots without collisions (which for example invoke the elevator reflex) or searching for ground and therefore accomplish a fluid motion. See algorithm 2 for a summary of the foot point detection method.

## IV. EXPERIMENTS

To verify the success of the described method, several experiments have been done. In order to be able to reconstruct the results, the first experiments were done indoors in an straightforward environment, which, however, provides geometrical characteristics the method has to cope with in unstructured terrain.

In order to prove the method's ability for proper acquisition of environmental features, a small test parcour with different levels of elevation was built; the characteristics of this environment should be easily recovered in the representation generated. LAURON III was sent into this parcour for mapping purposes: the machine walked into this dead end while scanning the ground approximately 40 cm in front of the robot's head, with it's right legs

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**Algorithm 2** Extraction of suitable foot positions  $P_p$  for the next step

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**Require:**  $P_l^i$ : actual foot positions of leg  $l$  ;  $(s_x, s_y, 0)$ : step direction vector

**for all** legs  $i$  that should perform a step **do**

$P_a = (x_a, y_a, z_a) = P_l^i$

$P_v = (x_a + s_x, y_a + s_y, z_a)$  {expected next foot position}

generate foot environment map  $L_{P_v}$  (algorithm (1))

determine  $\text{cred}(L_{P_v})$  according to equation (4)

**if**  $\text{cred}(L_{P_v}) < \text{cred}_{\min}$  **then** {map credibility too low}

invoke additional measurements around  $P_v$

generate foot environment map  $L_{P_v}$  (algorithm (1))

**end if**

find most suitable foot position  $P_p = (x_p, y_p)$  according to equation (5)

$z_p = h(L_{P_v}(x, y))$

determine parameters to move leg  $i$  to position  $(x_p, y_p, z_p)$

**end for**

pass parameters to behavior control module

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climbing across the obstacle. During the mapping process, no additional measurements are invoked to document the “pure” result of processing incoming data. Fig. 4 shows the test environment and the resulting overall map. Repeating the mapping process provided very similar maps, so the result is reproduceable.

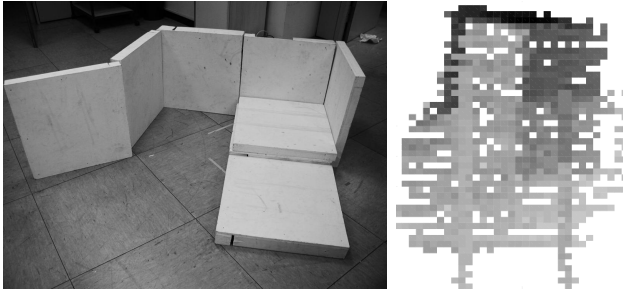


Fig. 4. The scenario to be explored and the map generated of the area. Darker cells indicate higher elevations, white cells are unclassified due to insufficient credibility.

It can be seen that the characteristics of the environment are reproduced fairly exactly in the map. Obstacles and elevation changes are detected correctly and the amount of unclassified cells is fairly low. The highest credibility values are found where more than one sensor contributed to the cell’s content; as a result, for example, no unclassified regions occur in the trace of the feet.

First outdoor tests reveal problems concerning the laser sensor under daylight conditions: due to massive reflections very many of the measurements turn out to be completely wrong. Because of that the incoming data is very sparse and not reliable. Figure 5 shows the an outdoor mapping effort and the resulting map: much of the cells are unclassified because the credibility values were too low. All classified cells, however, show definitely reliable possible foothold positions, and the robot is always able to find a place to set its foot on. Regarding the classified re-

gions, the characteristics of the environment are reflected: elevations levels are correct, and stumps and small bushes are recognized. Most notably, wherever data was acquired by the pressure sensors in the feet, the resulting credibility was absolutely satisfactory. As other experiments proved, this is enough information to enable the robot to perform a “follow the leader” strategy on its own. Given a foot map dimension that covers more than the distance between two adjacent legs, an initially empty map and no use of distance sensors, LAURON III places its hind feet on the only known places: the former positions of the forelegs.



Fig. 5. LAURON III performing an outdoor test run and the corresponding map of reliable foothold positions: due to massive light reflections much of the map is unclassified because the information is not credible enough. The trace of the feet, however, is not affected, and stumps and bushes (dark regions) are recognized. All shown cells represent possible positions to place the feet.

In another indoor experiment it could be proved that the adapted behavior control is able to cope with different elevation levels. LAURON III was able to manage another obstacle parcours with several different heights almost without collisions and very controlled motion up and down the steps (see fig. 6). Regarding the upward steps during a set of experiments, approximately 65 % of the step movements worked as expected, 5 % ended in a collision and about 30 % were so called “early positives”, which means that the leg rose too early to reach the elevation level, but succeeded in reaching the step with the second step without any collision. Those early positives occur only for the hind legs due to weak odometric information: the machine considers itself as having moved further than it really did and expects the elevation change too early<sup>3</sup>. Improvement of the actually prototypical odometric system is under current development, however, so early positives can be expected to vanish in the future. As another result, no ground-searching strategies were needed anymore when stepping down: the feet are moved down smoothly and directly.

All in all, despite odometric weaknesses, the experiment proved that the method is able to cope with the infor-

<sup>3</sup>The consequences of the weak odometry do also stand out in the map in figure 4: regarding the trace of the data acquired by the foot sensors, the trace clearly overlaps the area of the step.

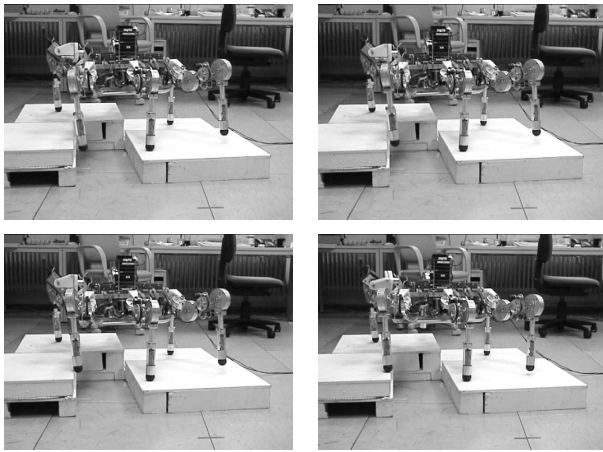


Fig. 6. LAURON doing a controlled and collision-free step upward an obstacle

mation collected. LAURON III's walking behavior could be improved significantly. Ground topology recognition abilities are good enough for suitable modification of the machine's walk. Its movements became more precise as hardly any collisions occurred and the performance of ground searching strategies were no longer necessary.

## V. CONCLUSIONS AND FUTURE WORKS

We presented a method for environment modeling, map building, and action selection concerning foothold position search for a walking robot that is supposed to operate in unstructured terrain.

Environmental data is acquired by the use of a laser and infrared sensor as well as pressure sensors in each leg. Merging the data of different sensor types provides robust and reliable perception of the environment. Collected data is stored in a data structure called *advanced inference grid*, which is based on the vector field histogram. It differentiates between occupancy and credibility information and therefore allows a distinction between geometrical and sensory uncertainties in information. Cell updates and sensor fusion are done using a fuzzy reasoning approach which proved to be efficient and of high quality as well as being easy to maintain. The resulting maps show good accuracy and are suitable for further processing purposes. Proper foothold positions can be easily extracted out of local foot environment maps in advance of each step, achieving a significant improvement of the machine's walking behavior. LAURON III is capable of overcoming obstacles precisely without collisions or the need for ground searching strategies.

After indoor tests proved promising and mapping efforts also worked well in unstructured terrain, verifying and improving the method's success in further outdoor experiments is the next main task, especially after having completed a better odometric system. Another current

research effort is to combine the method with stereo vision techniques to improve the recognition results and progress to landmark recognition and position corrections, and also porting the system on other machines as is currently done with the four legged walking machine BISAM [10].

## VI. ACKNOWLEDGEMENT

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