

# Autonomous Climbing of Spiral Staircases with Humanoids

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**Abstract**—In this paper, we present an approach to enable a humanoid robot to autonomously climb up spiral staircases. This task is substantially more challenging than climbing straight stairs since careful repositioning is needed. Our system globally estimates the pose of the robot, which is subsequently refined by integrating visual observations. In this way, the robot can accurately determine its relative position with respect to the next step. We use a 3D model of the environment to project edges corresponding to stair contours into monocular camera images. By detecting edges in the images and associating them to projected model edges, the robot is able to accurately locate itself towards the stairs and to climb them. We present experiments carried out with a Nao humanoid equipped with a 2D laser range finder for global localization and a low-cost monocular camera for short-range sensing. As we show in the experiments, the robot reliably climbs up the steps of a spiral staircase.

## I. INTRODUCTION

To fulfill high-level tasks such as delivery or home assistance, a robot must be able to autonomously operate in real-world settings and robustly navigate in complex indoor environments. This includes multi-level environments consisting of different floors connected by staircases.

Autonomous stair climbing with humanoid robots is a challenging task since humanoids typically execute motion commands only inaccurately. Reasons for this are that humanoids possess only a rough odometry estimate, they might slip on the ground depending on the ground friction, and backlash in the joints might occur. Additionally, the observations of their small and lightweight sensors are inherently affected by noise. This all can lead to uncertain pose estimates. However, to reliably climb up a complex staircase, the robot needs a highly accurate pose estimate on the stairs. Otherwise, it might risk a fall resulting from walking against a step or slipping off the stair edge after climbing up.

In this paper, we present a system in which the robot first estimates its global pose in a 3D representation of the environment and then tracks it over time. During stair climbing, the robot refines the pose estimate by detecting edges in images. These observed edges are associated with model edges that correspond to contours of individual stairs expected to be visible. The model edges are projected into the image given the estimated pose of the robot and the 3D model of the environment. The 3D model of the staircase can be learned by segmenting planes from a point cloud

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Fig. 1. *Left*: Our Nao humanoid is equipped with two low-cost monocular cameras and a Hokuyo 2D laser scanner on top of the head (photo: B. Schilling). We use 2D laser range data for globally localizing the robot and images of the lower camera (located below the eyes) for detecting edges corresponding to stairs. *Right*: Nao climbing up a spiral staircase using vision and laser data.

acquired by the robot while moving [1]. However, the learning process is not topic of this paper.

We present experiments with a Nao humanoid robot equipped with a 2D laser range scanner and a monocular camera. 2D laser data are used for global localization in an octree-based 3D representation of the environment. Our robot is able to climb up a spiral staircase, here consisting of ten steps. Except a scaling to match the robot's size, the environment is thereby unmodified, i.e., it does not contain fiducial points and the steps are not marked so as to be easily visually detectable.

In contrast to other approaches to humanoid stair climbing that require accurate stereo data [2], [3], an external tracking system [4], data from high-quality force/contact sensors [5], [6], or a manual pose initialization [7], our technique works successfully using only data from noisy, low-cost on-board sensors and works also for complex staircases, consisting of many steps and containing a spiral part.

This paper is organized as follows. After discussing related work in the following section, we introduce our humanoid robot platform in Sec. III. In Sec IV, we describe the 3D environment representation and the 6D localization system. Afterwards, we present in Sec. V our approach to stair climbing and show experimental results in Sec. VI.

## II. RELATED WORK

Nishiwaki *et al.* [8] developed toe joints for the humanoid H7. H7 was shown to climb single steps after manually positioning the robot in front of them. The robot did not integrate any sensory information to detect the stairs.

The approach developed by Honda for their ASIMO [5] uses a given model of the stairs and follows a fixed sequence of footsteps that is locally adapted using data from force

sensors. This strategy was shown to work successfully on a straight staircase. However, it is unclear whether it could be used for climbing up spiral staircases since in these scenarios more complex repositioning based on observations is needed.

Cupec *et al.* [9] proposed a vision-based approach to step upon obstacles. The obstacle detection technique relies on the assumption that obstacles and floor are clearly distinguishable to simplify edge detection. The authors presented experiments in which the robot Johnnie climbed two steps.

Gutmann *et al.* [2], [3] fit planes through 3D points generated from stereo data to recognize stairs. The stereo camera provides short-range data which is used to align the robot Qrio with the next step. Qrio was able to autonomously climb up and down a staircase with four small steps.

Chestnutt and Michel *et al.* [4], [7] plan footstep actions to climb staircases consisting of three steps with HRP-2. While the authors first made use of an external motion tracking system to get information about the environment [4], in their latter work [7], they developed a technique to visually track single objects that are in the camera field of view. This approach is also based on a given 3D model and a matching between detected and model edges is carried out. The method relies on a manual pose initialization and can only determine the pose of the robot relative to the tracked object, e.g., the staircase. In contrast to that, in our method the robot autonomously determines and tracks its global pose while navigating through the environment.

The most recent approach was presented by Chestnutt *et al.* [6]. Their robot is equipped with a nodding 2D laser range scanner located at the height of the hip, thereby acquiring 3D range data of the local environment. The authors propose to fit planes through 3D point clouds and construct a height map of the environment in which footsteps are planned. Their robot possesses six contact sensors at the bottom of the feet whose data is used for safe navigation. Only steps where all six sensors measure contact are executed. Experiments were presented in which the robot climbed two successive stairs.

Using the techniques presented in this paper, a comparably low-cost humanoid robot is able to climb up our spiral staircase with ten steps by estimating its global pose given data from on-board sensors and refining it using visual observations from a monocular camera.

### III. LASER-EQUIPPED NAO HUMANOID

In our experiments, we use a Nao humanoid [10] extended with a laser range finder. The Hokuyo URG-04LX laser is mounted in a modified head (see Fig. 1) and provides 2D range data within a field of view of  $240^\circ$ . By tilting the head, the robot can theoretically obtain 3D range data. However, this is time-consuming and there is a minimum distance of approximately 84 cm between the laser plane and the robot's feet while standing according to the construction (see Fig. 2). Thus, the 3D laser data cannot be used for detecting the next step immediately in front of the robot during stair climbing, but can be used to build a model of the complete staircase from a distance.

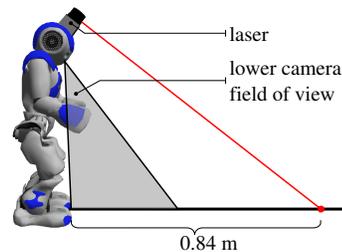


Fig. 2. Illustration of the robot indicating the laser plane and the field of view of the camera. As can be seen, there is a distance of 84 cm between the laser plane and the feet.

For exactly locating the next step and thus localizing the robot with a high accuracy, we make use of edges detected in the images of Nao's lower camera, which points  $40^\circ$  downwards. The camera has a diagonal field of view of  $58^\circ$ . We calibrated the camera so as to determine the intrinsic and distortion parameters. Knowledge about these parameters allows for transformations between 3D world and image coordinates.

With the laser head, Nao is 64 cm tall and weighs about 5 kg. The robot has 25 degrees of freedom. In order to obtain measurements of its joint positions, Nao is equipped with Hall effect sensors which measure the angle of each joint. Using the joints of the support leg, an estimate of the robot's torso position and orientation can be obtained through forward kinematics at any time. Additionally, an inertial measurement unit (IMU) yields an estimate about the robot's orientation. Measurements from a two-axis gyroscope and a three-axis accelerometer are integrated in order to obtain an estimate of the robot's torso orientation around the world's  $x$  and  $y$ -axis (roll and pitch, respectively). As further sensors, the robot possesses two bumpers, i.e., contact sensors located at the front of its feet.

## IV. ENVIRONMENT REPRESENTATION AND LOCALIZATION

### A. 3D Environment Representation

In non-planar multi-level environments, a full 3D occupancy grid map is necessary since the map needs to encode both occupied and free volumes. Throughout this work, we consider such a volumetric 3D representation of the environment as given. We use an octree-based multi-resolution representation that models occupied as well as free and unknown areas of the environment in a memory-efficient way [11].

### B. 6D Localization

For reliably completing navigation tasks including stair climbing, the robot needs to globally determine its pose in the environment and track it over time. Here, we briefly present our Monte Carlo localization (MCL) framework to globally determine and track the humanoid's full 6D pose in the 3D world model. For details, we refer to our previous work [12].

The complete 6D pose  $\mathbf{x} = (x, y, z, \varphi, \theta, \psi)$  consists of the 3D position  $(x, y, z)$  as well as the roll, pitch, and yaw

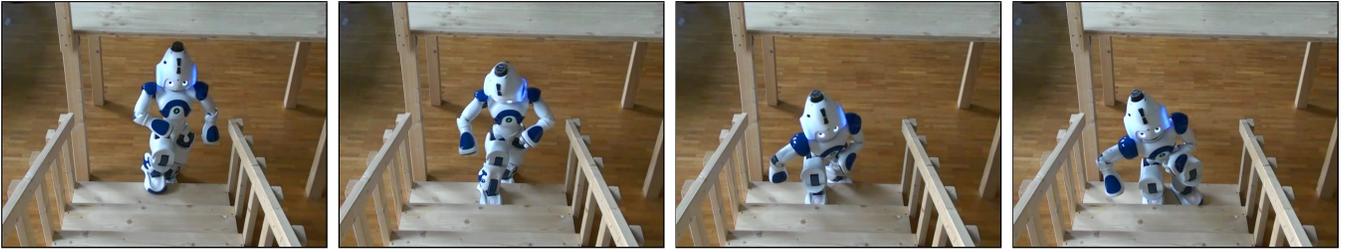


Fig. 3. Nao climbing a single stair of 7 cm height.

angles  $(\varphi, \theta, \psi)$  of the robot’s body reference frame in the 3D environment representation. This reference frame is located in the center of the humanoid’s torso, which is also the origin of all of its kinematic chains. To achieve a robust localization while walking and climbing stairs, we combine 2D laser data from the laser range finder located in the head, attitude data provided by the IMU, and information from the joint encoders. Odometry is computed from measured joint angles with forward kinematics and integrated in MCL with a Gaussian motion model.

In the observation model, we combine the data of the sensors into one observation  $\mathbf{o}_t$ : the 2D laser range measurements  $\mathbf{l}_t$  corresponding to a complete scan, the height  $\tilde{z}_t$  of the humanoid’s torso above the current ground plane as a measurement of its joint encoders, and the angles for roll  $\tilde{\varphi}_t$  and pitch  $\tilde{\theta}_t$  as estimated by the IMU. Since all these measurements are independent, the observation model decomposes to the product

$$p(\mathbf{o}_t | \mathbf{x}_t) = p(\mathbf{l}_t, \tilde{z}_t, \tilde{\varphi}_t, \tilde{\theta}_t | \mathbf{x}_t) = p(\mathbf{l}_t | \mathbf{x}_t) \cdot p(\tilde{z}_t | \mathbf{x}_t) \cdot p(\tilde{\varphi}_t | \mathbf{x}_t) \cdot p(\tilde{\theta}_t | \mathbf{x}_t). \quad (1)$$

Here,  $\mathbf{x}_t$  is the assumed state of the robot. In contrast to our previous approach [12], we use ray casting in the given volumetric 3D environment representation to compute the likelihood of individual beams  $p(l_{t,k} | \mathbf{x}_t)$ , which yields more accurate results compared to the endpoint model. In ray casting, it is assumed that beams from the robot’s sensor are reflected by the first obstacle they hit [13]. We determine the expected distance to the closest obstacle contained in the map for each beam given the robot pose and compare it with the actually measured distance. To evaluate the measurement and to model the measurement uncertainty of the sensor, we use a Gaussian distribution. Hereby, we consider the individual measurements  $l_{t,k}$  to be conditionally independent and compute the product of the corresponding beam likelihoods to determine  $p(\mathbf{l}_t | \mathbf{x}_t)$ .

Similarly, we integrate the torso height  $\tilde{z}_t$  above the ground plane as computed from the values of the joint encoders as well as the roll  $\tilde{\varphi}_t$  and pitch  $\tilde{\theta}_t$  provided by the IMU with a Gaussian distribution based on the measured values and the predicted ones.

While our localization method is highly accurate when walking on the ground [12], translational errors can be up to 3 cm while climbing the staircase.

## V. RECOGNIZING STEPS AND CLIMBING UP A SPIRAL STAIRCASE

In this section, we introduce our approach that combines the laser-based pose estimate with visual information to reliably climb stairs. First, we describe our technique to teach the robot the stair climbing motion.

### A. Learning to Climb a Single Stair

In this work, we assume that a model of the environment is given so that the height of the steps of the staircase is known in advance. This stair model can be extracted from 3D laser scans as we describe in our latest work [1]. With steps of the same height, the robot can execute the same stair climbing motion after positioning itself accurately in front of the next step.

We scaled the height of the individual steps relative to the size of the robot so that they have a realistic height of 7 cm. The scaled height is comparable to the height of steps for humans in the real world. Since the steps are still rather challenging to climb with the body plan of the robot, it has to execute a full body motion in order to keep its balance, i.e., it also has to move its torso, head, and arms. Note that the robot has a relatively high center of gravity due to the laser scanner located on top of the head.

We apply kinesthetic teaching to enable the robot to climb stairs. Here, we make use of *Choregraphe* [14], a graphical tool developed by Aldebaran Robotics, to program the Nao humanoid. In particular, we remove the stiffness from the joints and manually move the robot to statically stable poses during the stair climbing motion. The Hall effect sensors yield information about all joint angles at these poses. We record the corresponding keyframes and interpolate between them with Bézier curves to create smooth movements. Afterwards, we learn the timing to achieve a dynamically stable motion. This is done in simulation by evaluating different execution times.

The resulting motion enables the robot to climb stairs of the given height (see Fig. 3). Since the robot is symmetric, we mirror the motion in order to alternate the climbing leg during stair climbing which distributes the strain on the servos. There is only a small error margin, i.e., the robot has to be at most 1 cm away from the step, otherwise it falls backwards after reaching the level of the next step. Furthermore, the robot has to avoid bumping the stairs’ handrail with its arms so it should position itself within a range of 1 cm from the center of the stairs. Note that due

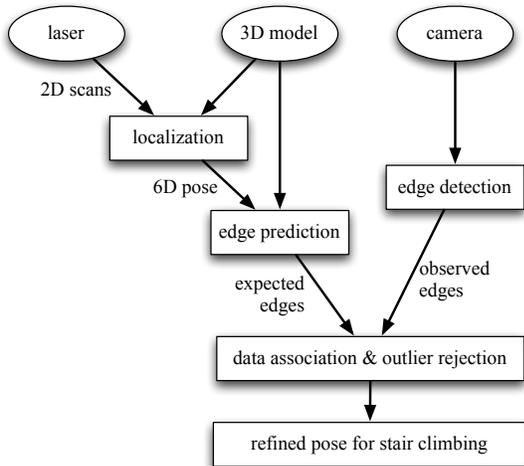


Fig. 4. Our system determines the robot’s global pose in a 3D world representation based on laser range observations. Afterwards, detected line segments in camera images are associated with model edges to recognize stairs and refine the pose estimate.

to inaccurately executed motion commands and slippage on the stairs, the robot might deviate from its planned motion. To deal with these challenges, we combine the laser-based localization with visual information to precisely localize the robot and accurately detect the next step as explained in the following.

### B. Recognizing Stairs

The laser-based localization system (see Sec. IV-B) yields a rather robust estimate about the robot’s 6D pose. However, relying solely on this information is not reliable enough for accurate positioning in front of the next step on the staircase. Thus, we combine the laser-based pose estimate with information extracted from the current camera image to accurately determine the robot’s pose during stair climbing.

As illustrated in Fig. 4, we use the estimated 6D robot pose and the given 3D environment representation to predict which model edges are in the current field of view of the camera. Additionally, we detect line segments in the camera images using the Canny edge detection algorithm in combination with the probabilistic Hough transform [15].

As next step, we have to match detected and model edges. To solve this data association problem, we project the predicted model edges into the camera image. We then assign costs to pairs of model and detected edges based on their distance and the difference in the angle and in the length of compared edges. Here, the length of model edges is computed by determining the length of the expected visible part of the edge. The distance of the line segments is determined as the distance of their centers. Accordingly, the cost  $c(d, m)$  of assigning a detected edge  $d$  to a model edge  $m$  is computed as

$$c(d, m) = \alpha \text{dist}(d, m) + \beta \text{angle}(d, m) + \gamma \text{length}(d, m), \quad (2)$$

where  $\alpha$ ,  $\beta$ , and  $\gamma$  are weights for the individual factors, which we experimentally determined so that the correct

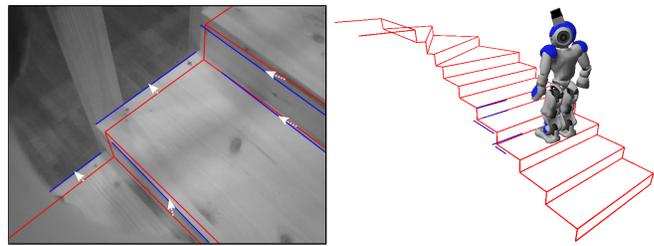


Fig. 5. *Left*: Model edges (red) and corresponding associated detected edges (blue). The model edges are projected into the camera image by using the 6D robot pose, which is estimated by our laser-based localization system. Note that texture of the wood was interpreted as step edge so that a misassignment occurs at the top of the upper stair. Furthermore, some relevant model edges could not be matched. To reduce the influence of falsely matched edges and failure detections, we analyze not only one image but a set of images. *Right*: Matched detected edges transformed into the 3D space model based on the pose estimate.

edges were matched in test images.

Finally, we associate each model edge with the detected edge leading to the lowest assignment cost according to Eq. 2. We do the same for each detected edge with the cheapest model edge and consider only those assignments which are mutually consistent. Fig. 5 depicts an example camera image with model edges and associated detected line segments.

To better deal with potential false detections, for example caused by shadows, we analyze several images and carry out the assignment process described above. In particular, the robot captures images from three different perspectives: straight to the next step, to the left, and to the right. For each captured image, we perform data association as described above. As a result, we have for each model edge  $i$  a set of associated detected line segments  $M_i$ : Let  $L_{\rightarrow i}$  denote the line segments detected in the left image and assigned to model edge  $i$

$$L_{\rightarrow i} = \{d_L \mid c(d_L, i) \leq c(d_L, j) \forall j \neq i\}, \quad (3)$$

$R_{\rightarrow i}$  and  $C_{\rightarrow i}$  accordingly for the right image and for the straight view. Thus,

$$M_i = L_{\rightarrow i} \cup R_{\rightarrow i} \cup C_{\rightarrow i}. \quad (4)$$

Each edge  $e \in M_i$  is then transformed into 3D world coordinates. This is directly possible since we know the height of the stairs from the 3D model and know on which stair the robot is currently standing. Finally, we apply the principle of random sample consensus (RANSAC) [16] to fit a line through all observed segments assigned to a model edge. Thus, we randomly sample line segments and fit lines through their endpoints. By means of RANSAC we are able to eliminate outliers wrongly assigned to model edges. Fig. 6 illustrates the final result of matching the detected line segments in the images from the three perspectives with model edges. Shown is the transformation of matched observed line segments into the 3D space.

We found that taking images with different head orientations improves the edge matching stability. This is because not all stair edges are visible from one point of view due to the camera’s narrow field of view. By considering the

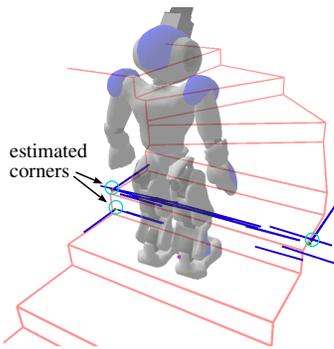


Fig. 6. Illustration of matched edges in the 3D space. The corners of the next step are estimated based on the intersection of fitted lines through the segments. Given these estimated corners, the robot’s pose is refined. The transformation into the 3D space is carried out given the estimated robot pose from the laser-based localization, which is also shown in this figure.

different images together with our RANSAC procedure, we are able to substantially increase the number of correctly detected and matched edges.

### C. Position Refinement for Stair Climbing

We now describe our approach to autonomous stair climbing by combining the techniques introduced above. When the robot is in front of steps based on the estimate of the laser-based localization, it turns the head to point its camera in the direction of relevant edges corresponding to the next step and captures images from three different perspectives.

We then accurately localize the robot relative to the next step based on the assignment of detected segments to model edges (see Sec. V-B). To do so, we determine the four corners of the vertical face of the step in front from the intersection points of the lines fitted with RANSAC. From the distance to these corners, the robot can accurately localize itself and compute the necessary movements to reach the starting pose for the stair climbing action.

For our learned stair climbing motion (see Sec. V-A), the ideal pose of the robot’s torso is 12 cm in front of the next step, centered and oriented perpendicular to the step edge. In the situation depicted in Fig. 6, the estimated robot pose according to the laser-based localization is closer to the next step than it is in reality. In this situation, our system determines the optimal starting pose to be 0.9 cm ahead of the robot with an orientational difference of  $9.9^\circ$  to the right. The robot then reaches this pose with an omnidirectional walking controller [17] and climbs the stair using the previously learned motion.

Since a fall may cause serious damage to the robot, it actively verifies its location relative to the next step by carefully touching it with its foot at the beginning of the climbing motion. Only if a bumper located at the front of its feet detects contact, the robot continues to climb the stair.

## VI. EXPERIMENTS

### A. Nao Climbing up a Spiral Staircase

First, we present an experiment carried out with our humanoid robot climbing up a spiral staircase consisting of ten steps and connecting the two levels of our environment.

The steps have a width of 60 cm, a height of 7 cm, and a depth of 18 cm (straight steps) and 21 cm at the center for spiral steps, respectively. Fig. 7 shows still frames of a video sequence<sup>1</sup> where our robot successfully climbs up the spiral staircase, thereby carefully looking for edges in order to reposition itself for the next step.

### B. Quantitative Evaluation

We now perform a quantitative evaluation of our approach for accurate positioning prior to climbing a stair. First, we evaluate the success rate of climbing up the spiral staircase.

Using only the laser-based localization, the robot is able to climb four subsequent stairs on average. Afterwards, its pose estimate is too inaccurate so that the stair climbing motion cannot be successfully executed anymore. Either the robot falls backwards or bumps into the handrail. In contrast, using our approach that refines the pose by matching detected edges in the images with model edges increases the success rate substantially. In ten real world runs on our spiral staircase consisting of ten steps, the robot successfully climbed 97% of the stairs (86 out of 89). Only one out of 89 stair climbing actions lead to a fall (the robot bumped the handrail with its shoulder). Here, the initial guess from the particle filter was too bad so that the correct edges were not in the camera’s field of view and thus wrong matchings occurred. In two further situations, the robot realized that it was not localized accurately enough and thus did not start to climb, so that the runs were aborted. In these cases, too few edges were detected so that the pose refinement was not successful. In the future, we plan to use mechanisms for active re-localization for these cases.

Furthermore, we evaluate the ability of our approach to identify the stair corners. This is done by detecting and matching line segments and by computing the intersection points of fitted lines. Here, for each stair, we determine the number of detected stair corners from which we compute the relative position to the next step. With three or more detected corners (55% of all detections), the robot can directly infer the target pose. With two corners, the remaining ones can be estimated from the step width given by the model. This was mostly the case in the spiral part of the staircase where the inner edges of the steps are comparably short (see Fig. 7). Only for 2% of the steps, too few line segments were detected so that no corners could be computed. Table I summarizes the results.

During our experiments, we observed that textured wood and shadows may be detected as edges. We found that a good initial guess for the matching, which is obtained from the robot’s localization, is important to accurately align the perceptions to the 3D model.

These results show that our approach enables a humanoid to reliably climb up the steps of complex staircases, which are not marked to be easily visually detectable. Furthermore, combining laser data with visual observations leads to a substantially more successful stair climbing behavior.

<sup>1</sup>Available online at <http://hrl.informatik.uni-freiburg.de>

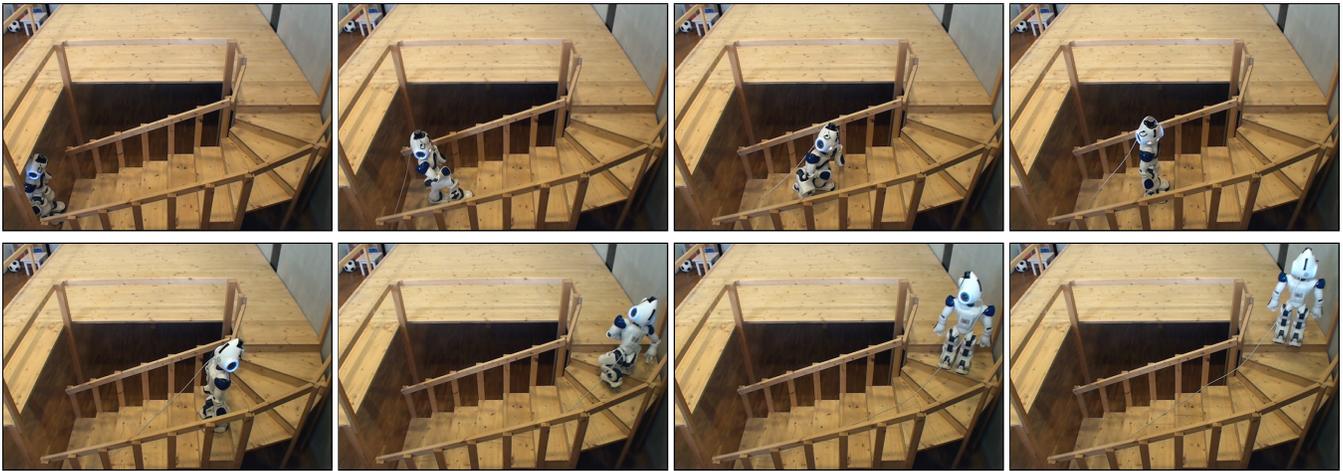


Fig. 7. Our Nao humanoid autonomously climbs up a spiral staircase with the proposed approach, which uses the pose estimate provided by laser-based localization and refines it by detecting and matching edges of stairs (left to right, continued in second row). A video of this sequence is available online at <http://hrl.informatik.uni-freiburg.de>.

TABLE I  
STAIR DETECTION RATE FROM EDGES

detected corners	stairs	
	total	percentage
all 4	7	8%
3	42	47%
2	38	43%
< 2	2	2%

## VII. CONCLUSIONS

In this paper, we introduced a technique to autonomously climb up complex staircases. In our approach, the humanoid initially estimates its global pose and tracks it over time in an a priori known 3D model. Based on the pose estimate and the model, edges corresponding to stair contours are projected into the images of a monocular camera. In this way, the robot is able to carry out a local matching between detected edges and model edges and refine its pose estimate to compute actions so as to reliably climb the next stair. In the experiments, we showed a Nao humanoid climbing up our spiral staircase with ten steps using the proposed approach. The appearance of the steps is thereby unmodified, i.e., the steps are not designed to simplify edge detection.

When relying only on the horizontal front edges of steps, our approach is also applicable to stepping down stairs. However, the Nao's body layout makes the design of a reliable stepping down motion far more challenging as it requires a dynamic falling motion which is not statically stable.

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