Adaptive Robot to Person Encounter by Motion Patterns

Hans Jørgen Andersen[1], Thomas Bak[2], and Mikael Svenstrup[2]

[1] Department for Media Technology, Aalborg University, 9220 Aalborg, Denmark
hja@cvmt.aau.dk
[2] Department of Electronic Systems, Automation & Control,
Aalborg University, 9220 Aalborg, Denmark
{tba,ms}@es.aau.dk

Abstract. This paper introduces a new method for adaptive control of a robot approaching a person controlled by the person's interest in interaction. For adjustment of the robot behavior a cost function centered in the person is adapted according to an introduced person evaluator method relying on the three variables: the distance between the person and the robot, the relative velocity between the two, and position of the person. The person evaluator method determine the person's interest by evaluating the spatial relationship between robot and person in a Case Based Reasoning (CBR) system that is trained to determine to which degree the person is interested in interaction. The outcome of the CBR system is used to adapt the cost function around the person, so that the robot's behavior is adapted to the expressed interest. The proposed methods are evaluated by a number of physical experiments that demonstrate the effectiveness of the adaptive cost function approach, which allows the robot to locate itself in front of a person who has expressed interest through his or hers spatial motion.

Keywords: Human-robot interaction, Adaptive Control, Social situatedness, Patterns of behavior.

1 Introduction

Technologies such as computing, visual recognition, and wireless connectivity open the door to a new generation of mobile robotic devices that see, hear, touch, manipulate, and interact with humans, potentially creating new interesting human living spaces that are productive, educational, safe and potentially enjoyable. Realizing this vision requires multidisciplinary research involving such areas as psychology, cognitive science, social sciences, computer science, robotics, and engineering. Current themes are discussed in [1].

Interaction between a robot and a human not only rely on the ability to input, output, and process information but also on the spatial relationship between the two actors. As an example most people would run away from a robot approaching at high speeds and most would be very suspicious about a robot approaching

A. Gottscheber et al. (Eds.): EUROBOT 2008, CCIS 33, pp. 1–11, 2009.

from behind. Quality interaction thus requires robot-human coordination in time and space; it requires that the robot can detect the person's interest in interaction and exhibit a behavior with respect for the person's privacy.

Several authors [2,3,4,5] have investigated people's willingness to engage in interaction with robots that exhibit different expressions or follow different spatial behavior schemes. In [6,7] models are reviewed that describe social engagement based on spatial relationships between a robot and a person with emphasis on the spatial movement of the actors. In [8] human-human proxemics distances were discussed and social and intimate zones defined. Social spaces between robots and humans were studied in [9] supporting the use of Hall's proxemics distances also in this context. A method for human-aware navigation using cost functions designed as Gaussian distributions centered around the person, is introduced in [10,11]. Besides the distance between the robot and the person the direction of approach is clearly also important and in [4,12] it is concluded that the preferred approach is from the front right or left and that a frontal and especially a rear approach should be avoided.

The focus of this paper is on determining a persons interest in interaction and adjusting the robot approach accordingly to reach an appropriate position. A person's willingness to engage in interaction is analyzed based on the person's spatial motion and knowledge from previous encounters stored in a case database. The case reasoning is based on [13,14] and facilitate a context aware generation of new cases of interaction. The robot behavior is controlled by a cost function adapted to the determined interest in interaction.

The human robot interaction methodology described in this paper, is supported by a number of experiments that demonstrate the effectiveness of the adaptive cost function approach. The case based reasoning and learning is demonstrated through a simulation study.

2 Materials and Methods

2.1 Evaluating Person Interest

Quality robot person interaction relies on an automatic detection of the person's willingness to interact. To accomplish this a person evaluator based on the motion of the person relative to the robot, is introduced. The philosophy of the evaluator is that if a person is interested in interaction the person will approach the robot whereas if the person is not interested he or she will have a trajectory away from the robot. However, these two extremes clearly have many levels in between where the interest of the person will be difficult to determine. In addition to person motion primitives, the temporal and spatial context of the person may influence the detection. To support this a person evaluator is designed as an adaptive Case Based Reasoning (CBR) system with the following variables as inputs (see Fig. 1):

Distance, $|d_{rp}|$, the distance between the person and the robot
Area, A_{eval}, the area spanned by the directional vector, v_{pers} and d_{rp}
Position, position of the person

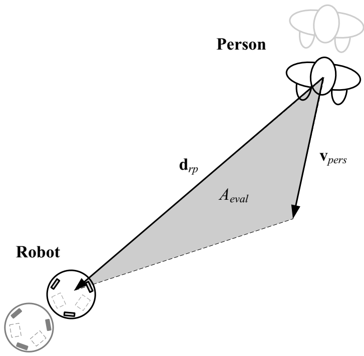


Fig. 1. Illustration of the input variables to the CBR system

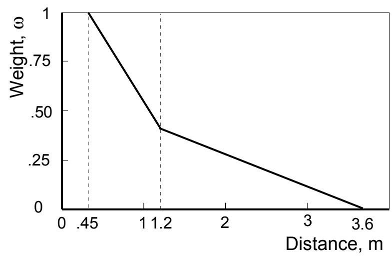


Fig. 2. Weights used for updating of the *PI* value. The Hall zones [8] are reflected by the 1.2 and 0.45 meter discontinuities.

The distance is used to emphasize that a large area at a large distance is less informative than a a large area at a small distance as indicated in Fig 2. The position is recorded in order for the robot to learn if people exhibiting the same kind of behavior, are most likely to be encountered in certain areas. The output of the CBR is a value $PI \in [0, 1]$, where 0 indicate no interest and 1 is an indication of absolute interest in interaction.

Given that a person has been detected and analyzed it remains to evaluate the persons willingness to interact using a case based approach. The task of specifying a case is a question of determining a distinct and representative set of features connected to the event of a human robot encounter. The outcome of the person detection and analysis, is a natural choice for inclusion in the case description. In addition, including position of the encounter will allow the robot to learn if people exhibiting the same kind of behavior, are most likely to be encountered in certain areas. By recording the time of day at time of detection, the robot may gradually become aware of possible similarities between the solution outcome i.e. whether assistance is needed or not at specific times.

Due to the active participation of the robot in evaluating a person, a number of temporary case lookups are performed, starting at 3.6 m distance and then every 10 cm. Two distinct databases are used. One serving as the main case library holding cases that have been evaluated by explicit expressions of interest, the other is a temporary case library functioning as storage of cases during approach. Each case has an associated *PI* which store the probability or indication of the detected persons interest to interact. During approach the *PI* of the cases in the temporary case library are used to control the approach. New cases have a default PI=0.5.

Whenever an outcome of the encounter is known, the temporary cases must be evaluated and afterwards erased. New cases are transferred to the main database for later reasoning. The database access is divided into two, being retrieval/reuse and revision/creation.

Retrieval/Reuse. When looking up in the main case library and no match is found the currently faced case is stored directly into the temporary case database. When a match is found the existing case is copied to the temporary case database, for later alteration of its indication when an outcome is known, i.e. during case revision. When searching for cases in the main database, rules must be set up to support case match. A case matches given that the case fields distance, spanned area, position and time of day all are within specified limits. All cases found to match are returned and stored in the temporary library in ascending order, after mismatch in spanned area.

Revision/Creation. Given that the robot has completed a person evaluation, and that the temporary case library, as a result of the performed case lookups, holds a given amount of cases. Whether the person evaluation has ended because of the person being evaluated as not interested or as a result of conducted communication, the robot should now revise all of the temporary stored cases. Thus, some cases should be created as new cases, while others should be used in updating existing cases.

Either way, the *PI* of the cases in the temporary case library are updated during revision according to the experienced outcome. The spatial relationship between human and robot must be considered when revising and creating new cases. The value of *PI* should naturally be strengthened as she or he is getting closer to the robot. Such weighted alteration has been implemented utilizing the behavioral zones as designated by Hall [8]. The weight as a function of the distance is illustrated in Fig. 2.

When entering the personal zone (1.2 meter) of the detected person, the weight function, w shifts resulting in a radical increase in weight according to distance.

Algorithm 1

```
Initially set all PI = 0.5
if (Interested) then
   PI = PI + wL
   if PI > 1 then
      PI = 1
else if (Not Interested) then
   PI = PI - wL
   if PI < 0 then
      PI = 0
```

Algorithm 1 outlines how *PI* is updated. According to Fig. 2, w is a weight that ensures that observations close to the robot are given a higher weight than observations further away. L is a learning rate factor that controls how much the *PI* is updated due to a new observation, i.e. a new observation should after a while only influence the *PI* value of the cases to a limited degree. Thus, the lower the learning rate, the less effect the weighing will have.

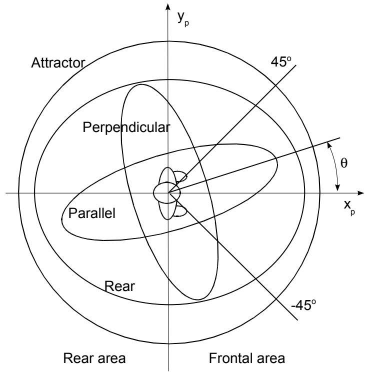


Fig. 3. Illustration of the four Gaussian distributions used for the cost function around the person. The rear area is behind the y_p axis. The frontal area is in front of the y_p axis which is divided in two, one in the interval from $[-45° : 45°]$ and the other in the area outside this interval.

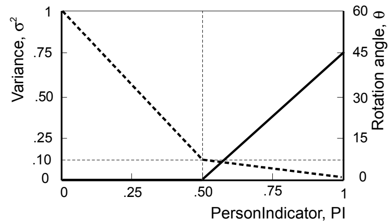


Fig. 4. Relation between the *PI* and variance σ^2 along the minor axis of the *Parallel* and *Perpendicular* distributions (solid line) and rotation angle θ (dashed line)

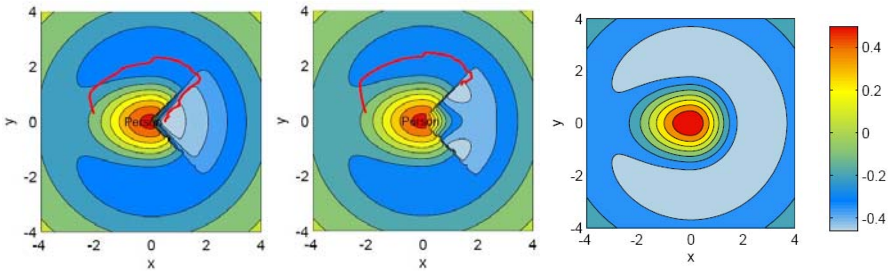
2.2 Adapting Robot Behavior

Given an indication of interest expressed by the *PI* value from the CBR system, the robot motion must be adjusted accordingly. The robot motion is controlled by an adaptive person centered cost function, which is the weighted sum of four Gaussian distributions which are adapted according to the *PI* value. The four Gaussian distributions are illustrated in Fig. 3 and has the following functions:

Attractor. This distribution is used to attract the robot to the person
Rear this distribution ensures that the robot does not approach a person from behind.
Parallel. This distribution is initially placed with its major axis parallel to the x_p-axis in the persons coordinate frame and adapting its variances and covariance according to the *PI* value.
Perpendicular. Distribution which initially is placed with its major axis perpendicular to the parallel distribution and adapting its variances and covariance according to the *PI* value.

The four distributions are combined resulting in a cost function landscape. The sum is divided into two areas, respectively, in front and behind the person. Behind only the sum of the *attractor* and *rear* distribution is considered. The values of the covariance for the two distributions are adjusted so the robot stays in Hall's public zone, i.e. 3.6 meters from the person and they are kept constant for all values of *PI*.

The *Parallel* and *Perpendicular* distributions are adapted according to the *PI* value, Hall's proximity distances, and the preferred robot to person encounter



(a) PI=1 (b) PI = 0.5 (c) PI=0

Fig. 5. Shape of the cost function for a person (a) interested, (b) maybe interested, and (c) not interested. Scale of the cost function is plotted to the left. The solid line in (a) and (b) illustrates the robot approach.

reported in [4,12] following the functions illustrated in Fig. 4. The width is adjusted by the value of the variances $\sigma^2_{x,y}$. The rotation θ may be adapted by adjustment of the covariance σ_{xy} according to $tan(2\theta) = \frac{2\sigma_{xy}}{\sigma_x^2 - \sigma_y^2}$.

The result is a change in size and rotation of the *Parallel* and *Perpendicular* distributions which given a *PI* value close to one may guide the robot into a position in front of the person, with an approach angle of approximately 45° given a *PI*. The resulting cost functions for specific values of *PI* are illustrated in Fig. 5.

2.3 Experimental Setup

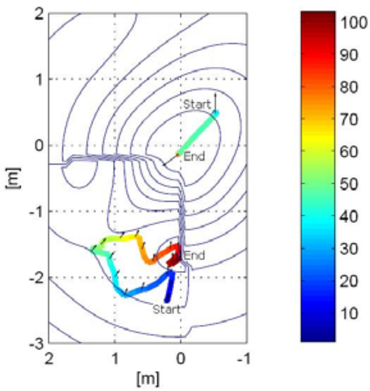
The proposed methods where implemented on a FESTO Robotino platform. On the platform the software framework Player[15] was installed. The robot is equipped with a URG-04LX line scan laser range finder together with a Creative Live! color Web camera.

The experiments were limited to only involve one person equipped with a pair of red socks in a controlled laboratory environment. For detection of the socks the color blob detection plug-in CMVision [16] was used. All experiments were recorded with a camera mounted in the ceiling and the trajectory of the person and robot were determined for reference.

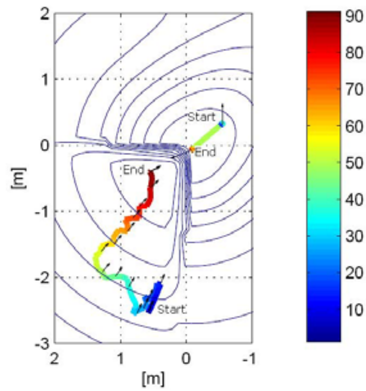
Training of the CBR system was done by simulation in Stage[15]. For this, the Player plug-in of the VFH+ method [17] together with the wavefront algorithm [15] was implemented to give a virtual person. In the training 20 series where run, 10 with a interested person and 10 with a not interested person.

3 Results

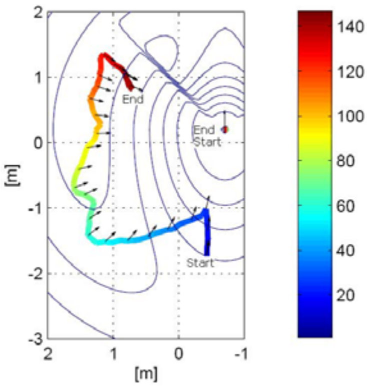
Figures 6 (a) and (b) illustrate the situation where the robot approaches a person from the front. In (a) the person is not interested in interaction whereas in (b) the



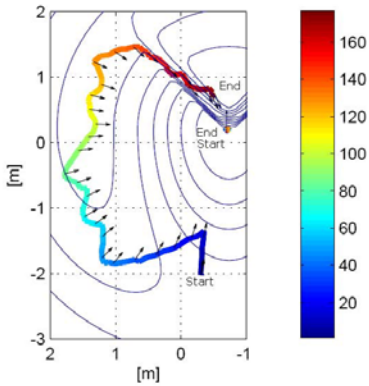
(a) not interested person



(b) interested person



(c) not interested person

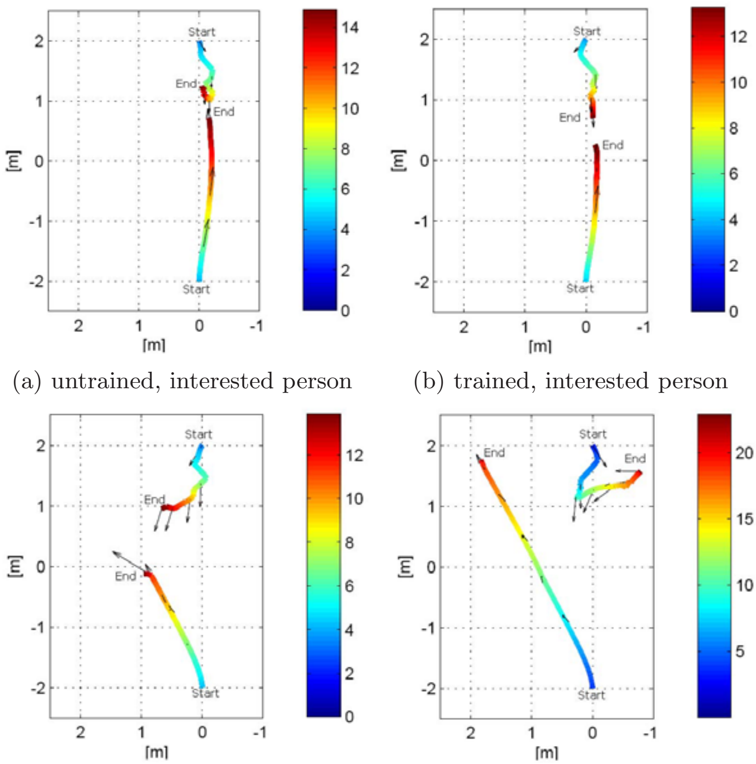


(d) interested person

Fig. 6. Trajectories generated from laboratory experiment. The bars indicate the time elapsed and the arrows indicate the heading of the robot and person. The contours illustrates the shape of the cost function at the end of the experiment.

person is. In both cases the robot initially observes the person and determines the person's direction of motion. After 40 seconds the motion of the robot changes according to the person interested in interaction, expressed by the *PI* value from the CBR system. In (a) the robot stops 1.5 meters away from the person and at an angle of 45° relative to the person's direction of motion. In (b) the cost function changes so the robot is allowed to face the person and stops at a distance of 0.7 meters directly in front of the person, ready for interaction.

Figures 6 (c) and (d) illustrate the cases where the robot approaches the person from behind. In (c) the person is not interested in interaction whereas in (d) the person is. In both cases the cost function forces the robot to move around the person according to the Hall distance. In (c) the robot stops 1.5 meters from the person and at an angle of 45° relative to the person's direction of motion. In (d) the cost function changes so the robot is allowed to directly face the person at a distance of 0.7 meters.



(a) untrained, interested person (b) trained, interested person

(c) untrained, not interested person (d) trained, not interested person

Fig. 7. Trajectories generated from simulated experiment. The bars indicate the time elapsed and the arrows indicate the heading of the robot and person. Behavior of the robot before and after training of the CBR system. For all experiments the robot starts at $(0, 2)$ and the person in $(0, -2)$. In the interested case the goal position of the robot is set to the person position whereas in not interested case the simulated person is set to goto $(2, 2)$.

To demonstrate the learning abilities, the results of simulated experiments are given in Fig. 7. Results of the robot behavior before and after training are illustrated for a situation where the person is not interested in interaction.

Comparing the behavior of the untrained and trained robot there is a significant change in the robots behavior after training. The motion of the robot does not deviate significantly at large distances due to the lower weighting of observation far from the robot and as a result the *PI* will have a value of approximately 0.5 for both situations. As the distance between robot and person is reduced as in (a) (at about 2 meters or after 9 seconds), the untrained robot starts to reverse while deviating to the right. This is because the forward part of the cost function is not rotated as the person interest indication is not yet changed from the default value of 0.5, i.e. the cost appears is a in Fig. 5(b). However,after training the robot evaluates the person as interested and the forward part of the cost function is rotated, allowing the robot to approach the person frontally, i.e. the cost function is adapted to appear as in Fig. 5(a).

In Fig. 7(d) the robot assumes that the person is interested (as this is default) and approaches the person until it prevents the person from continuing towards the goal which is set to $(2, 2)$. However, after training the robot evaluates the behavior of the person as not interested and as a result the PI takes a values of 0 coursing the cost function to appear as in Fig. 5 (c). The result is that the robot is pushed away from the person so the person is able to reach the position $(2, 2)$ without interference by the robot.

4 Discussion

The results above demonstrate how an adaptive Gaussian cost function may be used as the basis for a spatial robot behavior scheme on a planar surface. Given the determination of a person's pose this may be combined with knowledge about the person's interest to reshape the cost function and drive the robot into a position which the designer has determined as appropriate for quality approach and interaction. The adaption may be extended to also include robot speed in regard to the distance.

The method is relying on the pose of the person which clearly limits the method as a person standing still may have a direction frontal to the robot while the robot assumes the worst case and assumes it is approaching from the back. However, a pose detection system based on computer vision could easily be integrated into this approach.

To incorporate experiences from encounters the simulated experiment has demonstrated how a CBR system may be trained and used to automatically adapt the Gaussian cost function. Training was demonstrated to significantly change the robots spatial behavior, clearly generating trajectories that do not interfere with person's not interested in interaction. The case database is set up to support future extensions such as location and time.

Further extensions would naturally include the implementation of multi media information as speech and gesture recognition, all variables that may be included in the CBR-system.

In general the results shows a behavior of the robot as expected. Clearly, the experimental work is quite limited and the final proof of concept involving random person's still needs to be done. Before fully integration of the sensors necessary for such experiments hybrid test as "wizard of oz" or semi controlled experiments where the robot is interactively given the information it is lacking, due to limited sensor support, may be conducted.

5 Conclusion

This paper has described and demonstrated by experimentation a spatial robot behavior scheme that supports elements to ensure quality human-robot interaction. A person centered adaptive cost function based on summation of four

Gaussian distributions adjusted to the person's interested in interaction, is introduced. For adjustment of the cost function a novel person evaluator method based on solely the motion of the person, is introduced. The patterns of behavior is further used to train a CBR-system for learning and adaptation of robot motion to a given situation. The proposed control scheme is evaluated by a number of physical experiments that demonstrate the effectiveness of the adaptive cost function approach, which allows the robot to locate itself in front of a person who has expressed interest through his or hers spatial motion.

References

1. Dautenhahn, K.: Methodology & themes of human-robot interaction: A growing research field. International Journal of Advanced Robotic Systems 4(1), 103–108 (2007)
2. Bruce, A., Nourbakhsh, I., Simmons, R.: The role of expressiveness and attention in human-robot interaction. In: Proceedings, AAAI Fall Symposium (2001)
3. Christensen, H.I., Pacchierotti, E.: Embodied social interaction for robots. In: Dautenhahn, K. (ed.) AISB 2005, Hertsfordshire, April 2005, pp. 40–45 (2005)
4. Dautenhahn, K., Walters, M., Woods, S., Koay, K.L., Sisbot, E.A., Alami, R., Siméon, T.: How i serve you? a robot companion approaching a seated person in a helping context. In: HRI Human Robot Interaction 2006 (HRI 2006), Salt Lake City, Utah, USA (2006)
5. Hanajima, N., Ohta, Y., Hikita, H., Yamashita, M.: Investigation of impressions for approach motion of a mobile robot based on psychophysiological analysis. In: IEEE International Workshop on Robots and Human Interactive Communication ROMAN 2005, August 2005, pp. 79–84 (2005)
6. Michalowski, M., Sabanovic, S., Simmons, R.: A spatial model of engagement for a social robot. In: The 9th International Workshop on Advanced Motion Control, AMC 2006, Istanbul (March 2006)
7. Michalowski, M., Sabanovic, S., DiSalvo, C., Busquets, D., Hiatt, L., Melchior, N., Simmons, R.: Socially distributed perception: Grace plays social tag at aaai 2005. Autonomous Robots 22(4), 385–397 (2007)
8. Hall, E.: The Hidden Dimension. Doubleday (1966)
9. Walters, M.L., Dautenhahn, K., te Boekhorst, R., Koay, K.L., Kaouri, C., Woods, S.N., Lee, D., Werry, I.: The influence of subjects' personality traits on personal spatial zones in a human-robot interaction experiment. In: Proc. IEEE Ro-man, Hashville, August 2005, pp. 347–352 (2005)
10. Sisbot, E.A., Clodic, A., Urias, L., Fontmarty, M., Bréthes, L., Alami, R.: Implementing a human-aware robot system. In: IEEE International Symposium on Robot and Human Interactive Communication 2006 (RO-MAN 2006), Hatfield, United Kingdom (2006)
11. Sisbot, E.A., Alami, R., Siméon, T., Dautenhahn, K., Walters, M., Woods, S., Koay, K.L., Nehaniv, C.: Navigation in the presence of humans. In: IEEE-RAS International Conference on Humanoid Robots (Humanoids 2005), Tsukuba, Japan (December 2005)
12. Woods, S., Walters, M.L., Koay, K., Dautenhahn, K.: Methodological issues in hri: A comparison of live and video-based methods in robot to human approach direction trials. In: The 15th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN 2006), Hatfield, UK, September 2006, pp. 51–58 (2006)

13. Kolodner, J.: Case-based reasoning. Morgan Kaufmann Publishers Inc., San Francisco (1993)
14. Ram, A., Arkin, R.C., Moorman, K., Clark, R.J.: Case-based reactive navigation: A case-based method for on-line selection and adaptation of reactive control parameters in autonomous robotic systems. IEEE Transactions on Systems, Man, and Cybernetics 27, 376–394 (1997)
15. Collett, T.H., MacDonald, B.A., Gerkey, B.P.: Player 2.0: Toward a practical robot programming framework. In: Sammut, C. (ed.) Proceedings of the Australasian Conference on Robotics and Automation (ACRA 2005), Sydney, Australia (December 2005), `http://playerstage.sourceforge.net`
16. Bruce, J., Balch, T., Veloso, M.: Fast and inexpensive color image segmentation for interactive robots. In: Proceedings of IROS 2000, Japan (October 2000)
17. Ulrich, I., Borenstein, J.: Vfh*: Local obstacle avoidance with look-ahead verification. In: IEEE International Conference on Robotics and Automation, San Francisco, April 2000, pp. 2505–2511 (2000)