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Published in:
The 18th IEEE International Symposium on Robot and Human Interactive Communication, 2009. RO-MAN 2009

DOI (link to publication from Publisher):
10.1109/ROMAN.2009.5326212

Publication date:
2009

Document Version
Publisher's PDF, also known as Version of record

The 18th IEEE International Symposium on
Robot and Human Interactive Communication
Toyama, Japan, Sept. 27-Oct. 2, 2009

Adaptive Human aware Navigation based on Motion Pattern Analysis

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Abstract— **Respecting people's social spaces is an important prerequisite for acceptable and natural robot navigation in human environments. In this paper, we describe an adaptive system for mobile robot navigation based on estimates of whether a person seeks to interact with the robot or not. The estimates are based on run-time motion pattern analysis compared to stored experience in a database. Using a potential field centered around the person, the robot positions itself at the most appropriate place relative to the person and the interaction status. The system is validated through qualitative tests in a real world setting. The results demonstrate that the system is able to learn to navigate based on past interaction experiences, and to adapt to different behaviors over time.**

I. INTRODUCTION

The vision of robots participating in our day-to-day lives is a main part of the focus in the research field of Human Robot Interaction (HRI) [5]. The vision is supported by progress in computing, visual recognition, and wireless connectivity, which open the door to a new generation of mobile robotic devices that see, hear, touch, manipulate, and interact with humans [8].

Consider a robot supporting care assistants. At one time of the day, the support may include handing out food. In this case, the robot will interact closely with the care assistants and the persons being assisted. After a while, the persons around the robot will not need its assistance anymore and hence its behavior should be adjusted according to this new situation. For a robot to behave naturally in such situations, it will be necessary for it to learn from experiences and to adapt its behavior to the person's desire to interact.

To incorporate the ability to learn from experiences, researchers [13] have investigated Case Based Reasoning (CBR). CBR allows recalling and interpreting past experiences, as well as generating new cases to represent knowledge from new experiences. To our knowledge, CBR has not yet been used in a human-robot interaction context, but has been proven successful solving spatial-temporal problems in robotics in [12]. CBR is characterized by its adaptiveness making it well suited for implementing an adaptive behavior on a human interactive robot, as described in the case above. Hidden Markov Models and Bayesian inference algorithms have successfully been applied for modeling and predicting spatial user information [9], but a clear advantage of using CBR is the simple implementation and the relatively little need of parameter tuning.

We introduce a simple, robust and adaptive system for detecting whether a person seeks to interact with the robot based on the person's pose and position. We define a human's pose as the position and orientation of the body, and infer pose from 2D laser range measurements as explained in [16]. Other researchers [14] have investigated the use of laser scanner input and head pose information from a camera, but the approach here is limited to only using a laser scanner.

When the probable outcome of a person-robot interaction has been determined by the robot, it is used as a basis for human-aware navigation respecting the person's social spaces as discussed in [6]. Several authors [2], [3], [6], [11] have investigated the willingness of people to engage in interaction with robots that follow different spatial behavior schemes. In the method described here, navigation is done using potential fields which has shown to be useful for deriving robot motion [15], [7]. The implemented adaptive navigation behavior is described further in detail in [1], [16]. The adaptive CBR and navigation methods have been implemented and tested in a real world human robot interaction test setup.

II. MATERIALS AND METHODS

The robot behavior described in this paper is inspired by the spatial relation between humans (proxemics) as outlined in [10]. Hall divides the zone around a person into to four categories according to the distance to the person:

- the public zone $> 3.6m$
- the social zone $> 1.2m$
- the personal zone $> 0.45m$
- the intimate zone $< 0.45m$

Social spaces between robots and humans were studied in [17] supporting the use of Hall's proxemics distances.

In order for the robot to be able to position itself in the most appropriate position relative to the person, it should be able to estimate what will be the outcome of the human-robot interaction during run-time. If it is most likely that the person do not wish to interact, the robot should not violate his or hers personal space but seek to the social or public zone. On the other hand, if it is most likely that the person is willing to interact with the robot, the robot should try to enter the personal zone.

To accomplish this behavior an evaluator based on the motion of a person relative to the robot is introduced. The philosophy of the evaluator is that:

This work was not supported by any organization

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- There is a correspondence between human motion pattern relative to the robot, and the likelihood of close human-robot interaction.
- This correspondence can be automatically estimated based on continuously provided pose and position estimates, together with stored interaction information from previous experiences.

The output from the evaluator can be used to control the robot and enable it to navigate to an appropriate position relative to the person.

A. Evaluating human robot encounters

The central output from the person evaluator is the continuous variable *PI* which indicates what the robot believes will be the outcome of the human behavior at the current time (1 = close interaction, 0 = no close interaction). *PI* does not denote a probability but is a fuzzy predicate defined to denote to which degree the person is likely to seek close interaction with the robot.

The adaptive person evaluator is designed based on Case Based Reasoning (CBR). The CBR system is basically a database describing each encounter. Specifying a case in CBR is a question of determining a distinct and representative set of features of the human robot encounter. In order to ensure simplicity, we have selected to rely on the simple features position and pose only. More advanced features such as person identification, gesture and facial recognition could be incorporated in the database but is considered out of scope here. The used features are illustrated in Fig. 1, where:

Case, is a reference number of each case
x, is the x coordinate of the position of the person in the robot's coordinate system, sampled in 40 cm intervals
y, is the corresponding y coordinate of the position, also sampled in 40 cm intervals
θ, is the pose of the person sampled in an angular resolution of 0.2 radian = 11.5 degrees.
PI, is the value estimated by the CBR system.

The features **x**, **y** and θ are all stored in a precision which facilitates match-making when performing database queries. The database does not hold any explicit information about context or environment.

The starting point of the CBR system is an empty database holding no a priori correspondence between trajectories and probability of interaction. Interaction is identified if the person hands over an object to the robot within a time period. If the person disappears from field of view of the robot or if no hand over has occurred within this time limit, no interaction is said to occur. There are basically two different stages of the robot operation.

1) A person encounters the robot, and the robot evaluates the person given all the previous experiences from the database.
2) The robot updates the database according to a person encounter, which has just passed.

When evaluating a person, a number of case lookups are performed starting at 4 m distance and afterwards for each

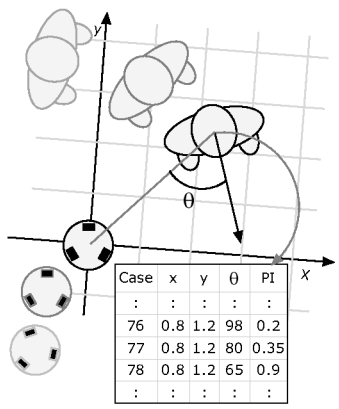


Fig. 1. Illustration of the input variables to the CBR system and the corresponding output *PI* stored in the CBR database.

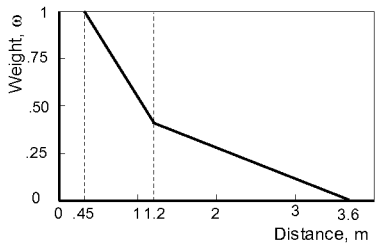


Fig. 2. The figure shows the weight ω as a function of the distance between the robot and the test person. ω is a weight used for updating the level of interest *PI*

0.1 second. Initially, when a person is identified, the *PI* is set to 0.5, which indicates that the robot is not sure what is going to happen. Each time a case lookup is performed and a matching case is found, the *PI* value is updated using a first order autoregressive filter ensuring that past values of *PI* is reflected in the update. The consequence is that the entire trajectory history is reflected in the current value of *PI*. If for example a matching case is found where $PI = 1$ and the current value for the person is $PI = 0.5$, then *PI* is updated to a larger value. If the looked up case has e.g. $PI = 0$, then the current *PI* is decreased from 0.5 to a lower value. Because the robot updates the database after the encounter of all new experiences, the system gradually learns how to decode trajectories into *PI* values between 0 and 1.

A weight function is introduced in order for the robot to pay more attention to the reactions of the detected person the closer he/she is to the robot [1]. Such weighted alteration has been implemented utilizing the behavioral zones as designated by Hall [10] and the weight as a function of the distance between the robot and the test person is illustrated in Fig. 2.

Algorithm I outlines how *PI* is updated. The weight factor w ensures that observations close to the robot are given a higher impact on the database than observations further away. L is a learning rate that controls the temporal update of *PI*, i.e. how much *PI* should be updated due

to a new observation. The closer L is to zero, the more conservative the system is and the less *PI* will be affected by new observations. In a progressive setup, L is close to 1 and consequently *PI* will adapt faster.

Algorithm I

```
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
```

B. Human-aware Navigation

The human-aware navigation is described in detail in [1], [16], and is here briefly summarized.

For modeling the robots navigation system, a person centered potential field is introduced. The potential field is calculated by the weighted sum of four Gaussian distributions of which one is negated. The covariance of the distributions are used to adapt the potential field according to *PI*.

In the extreme case with $PI = 0$, the potential field will like look Fig. 3(a). Using the method of steepest descent, the robot will move towards the dark blue area, i.e. the robot will end up at the lowest part of the potential function, approximately 2 meters in front of the person. The other end of the scale with *PI*=1, is illustrated in Fig. 3(c). Here the person is interested in interaction, and as result the potential field is adapted such that the robot is allowed to enter the space right in front of him or her. In between Fig. 3(b) is the default configuration of $PI = 0.5$ illustrated. In this case the robot is forced to encounter the person in approximate $45°$, according to [6], [18] studies.

III. Experimental Setup

The basis for the experiments was a robotic platform from FESTO called Robotino. The robot is equipped with a head having 126 red diodes (see Fig. 4) which enables it to express different emotions. The robot is 1 meter high, and has mounted an URG-04LX line scan laser placed 35 cm above ground level, scanning 220 degrees in front of the robot. In order to get feedback from the test person, a simple on/off switch was placed just below the robot's head, 75 cm above ground level. The software framework Player [4] was installed on the platform and used for control of the robot and implementation of the CBR system.

To detect persons the robot rely on the scans from the laser range finder using the leg detection algorithm presented in [19]. The algorithm is further supported by a Kalman filter for tracking and estimation of the person pose [16].

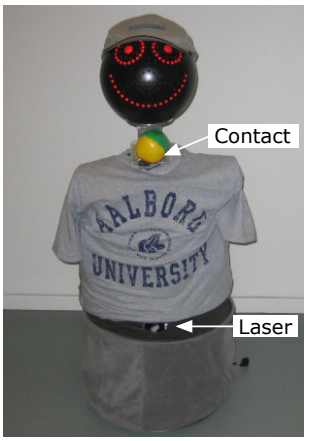


Fig. 4. The modified FESTO Robotino robotic platform.

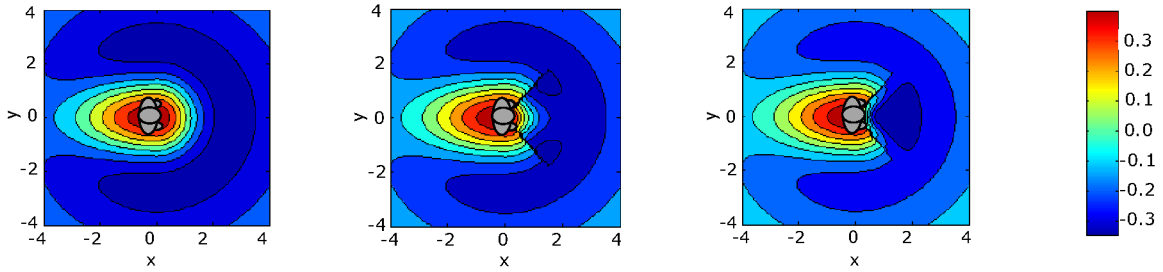
Experiments. Evaluation of the proposed method were performed through two experiments:

In experiment 1, the objective was to see if estimation of *PI* can be obtained based on interaction experience from different persons. The test should illustrate the learning ability of the system, making it able to predict the outcome of the behavior for one person based on former experience from others. A total of five test persons were asked to approach or pass the robot using different motion patterns (see Fig. 5). The starting and end point of each trajectory were selected randomly, while the specific route was left to the own devices of the test person. The random selection was designed so the test persons would end up interacting with the robot in 50% of the cases. In the other 50% of the cases, the test persons would pass the robot either to the left of the right without interacting. The output values (*PI*), the input values (position and pose), and the database were logged for later analysis.

In experiment 2, the objective was to test the adaptiveness of the method. The system should be able to change its estimation of *PI* over time for related behavior patterns. A total of 36 test approaches were performed with one test person. The test person would start randomly in P1, P2 or P3 (see Fig. 5) and end his trajectory in P5. In the first 18 encounters the test person would indicate interest, while in the last 18 encounters the person did not indicate interest. The output values (*PI*), and the input values (position and pose) were logged for later analysis.

The test took place in a foyer at the University campus with an open area of 7 times 10 meters. This allowed for easily repeated tests with no interference from other objects than the test persons. If the test persons passed an object to the robot, they would activate the on/off switch, which was recognized as interaction by the system. If the test person did not pass an object within 15 seconds or disappeared from the robot field of view, this was recognized as if no close interaction had occurred. The test persons were selected randomly among the students from campus. None had prior knowledge about the implementation of the system.

For all experiments, a learning rate of L = 0.3 was used.



(a) PI=0, person not seeking interaction (b) PI=0.5, interaction unclear (c) PI=1, person seeking interaction (d) Scale

Fig. 3. Shape of the potential field. The scale for the potential field is plotted to the right. The robot seeks towards the point with the lowest value.

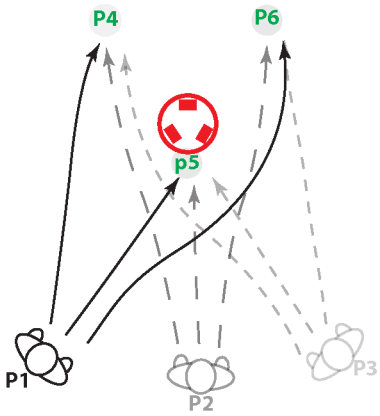


Fig. 5. Illustration of possible pathways around the robot during tests. A test person starts from either point P1, P2 or P3 and passes either P4, P5 or P6. If the trajectory goes through P5, an interaction occurs by handing over an object to the robot

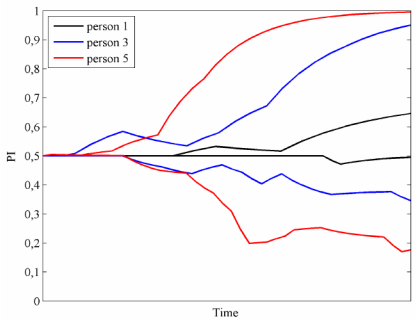


Fig. 7. The figure shows *PI* as a function of time for three test persons. For each test person, *PI* is plotted for an encounter where interacting occurs and for an encounter where no interaction occurs.

The result was a fairly conservative learning strategy, giving a clearer illustration of the development of *PI*.

IV. Results

A. Experiment 1

The starting point of the CBR system is an empty database. As robot-person encounters get registered by the robot, the database gradually gets filled with cases. All values in the database after different stages of training are illustrated by four-dimensional plots in Fig. 6. The first two dimensions are the dots in the 40 by 40 cm grid, which illustrate the position of the person in robot coordinate frame. At each position, the direction of the person is illustrated by a vector. The color of the vector denotes the value of *PI*. Blue color indicates that the person does not seek interaction, while the red color indicates that the person seeks interaction, i.e. $PI = 0$ and $PI = 1$ correspondingly. A green vector indicates $PI = 0.5$.

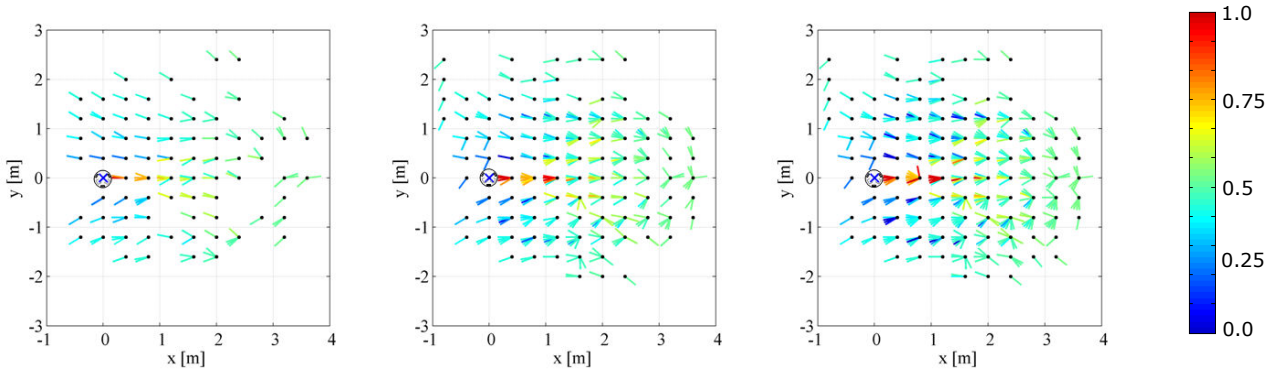
Fig. 6(a-c) illustrates the development of the database for the 5 test persons. Fig. 6(a) shows all cases after one test person, Fig. 6(b) after 3 test persons and finally Fig. 6(c) shows all cases (around 500) after 5 test persons.

In Fig. 7, the probability indicator *PI* for one specific encounter is plotted as a function of time. This is done for test person 1, 3 and 5. *PI* is plotted twice for each test person; once for a randomly selected encounter where the test person is interacting with the robot, and once for a random selected encounter where the test person passes the robot without interacting. For the first test person, it can be seen that *PI* increases to a maximum around 0.65 for an encounter ending with a interaction. For the same test person, it can be seen that *PI* drops to a minimum of 0.48 for an encounter where no interaction occurs. For the 3rd test person, *PI* ends with a value around 0.9 for an encounter where interaction has occurred, while $PI = 0.35$ for an encounter where no interaction has occurred. For the last test person, *PI* rapidly increases to a value around 1 for an encounter where interaction occurs, and has *PI* around 0.18 when the person does not interact. Each run takes between 2 and 4 seconds depending on the velocity of the user. Changes in *PI* can be seen in first quartile of each run, while maximum (or minimum) is not reached before fourth quartile.

B. Experiment 2

This test should show that the estimation of *PI* can adapt over time to different interaction outcome. Stored values for *PI* in the database have been calculated as an average for three areas (see Fig. 8) after each encounter:

- The frontal area of the robot (area 1)
- The small area including the frontal area (area 2)
- All cases stored in the database (area 3)



(a) After 1st test person (b) After 3rd test person (c) After 5th test person (d) *PI*

Fig. 6. The figures show the values stored in the CBR system after completion of the 1st, 3rd and 5th test person. The robot is located in the origin (0,0), since the measurements are in the robot coordinate frame. Each dot represents a position of the test person in the robot coordinate frame. The direction of the movement of the test person is represented by a vector, while the level (*PI*) is indicated by the color range.

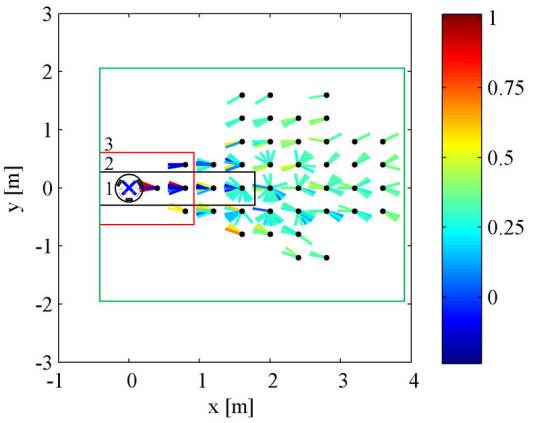


Fig. 8. The figure is a snapshot of the database after the second experiment was done. It shows how the mean value for *PI* is calculated for three areas: 1) the frontal area, 2) the small area and 3) for all cases. The development of the mean values over time for all three areas are illustrated in Fig. 9

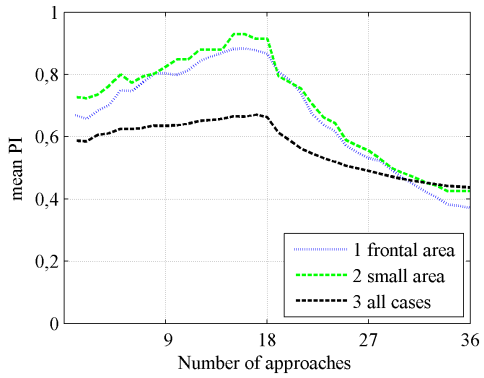


Fig. 9. Illustrates how the mean of *PI* evolves for the three areas indicated in Fig. 8 for 36 person encounters for one test person.

Fig. 9 shows the development of *PI* for 36 person encounters for one person.

As can be seen from Fig. 9, the mean value of *PI* increases for the first 18 encounters - especially for the frontal and small area having a maximum value at 0.9 and 0.85 correspondingly, but less for the mean for all cases (around 0.65). After 18 encounters, *PI* drops for all areas. Most notable, the frontal area drops to a minimum of 0.39 after 36 encounters. Although *PI* also drops for the small area, it does not fall to a value less than 0.42 which is approximate the same as for all cases 0.43 which has the smallest descent.

V. Discussion

The results demonstrate that using pose and position as input to a CBR system, it is possible to evaluate the behavior of a person adequately for human aware navigation system.

As can be seen in Fig. 6(a-c), the number of plotted vectors increases as more and more cases are stored in the database. This shows the development of the CBR system, and clearly illustrates how the CBR system gradually learns from each person encounter. The number of new cases added to the database is highest in the beginning of the training period where few (or no) case matches are found. As the training continues, the number of new cases added to the database is reduced as matching cases are found and therefore causes an update. The growth of the database when training depends on the resolution of the selected case features and the time and complexity of the training scenario. Based on current experiments there are no indications that the size of the database will grow inappropriately. The system could be enhanced by incorporating information about the environment or the interaction context thereby accommodation more realistic cluttered environments. In Fig. 6(a-c), it can be seen that the vectors are gradually turning from either red or blue to green as distance increases. This is expected, because the weight with which *PI* gets updated, is as a function of the distance between the robot and test person (see Fig. 2). This

is reasonable as it gets more difficult to assess human interest at long distance.

In all three figures, the vectors in the red color range (high *PI*) are dominant when the direction of the person is towards the robot, while there is an overweight of vectors not pointing directly towards the robot in the blue color range (low *PI*). This reflects that a person seeking interaction has the trajectory moving towards the robot.

Fig. 7 shows the development of *PI* over time when one test person changes behavior. It can be seen how maximum and minimum values for *PI* increases as more test persons have been evaluated. After evaluating one test person, the robot has gathered very little interaction experience, and thereby has difficulties in determining the correspondence between motion pattern and end result - hence *PI* stays close to 0.5. After the third test person has been evaluated, the robot now has gathered more cases and therefore has improved estimating the outcome of the behavior. For the last test person, the robot is clearly capable of determining what will be the outcome of the encounter.

Fig. 9 shows the development of *PI* over time. It can be seen that *PI* changes more for the frontal area and small area than for all other cases. This is because most cases will be close to 0.5 at large distances, which affects the mean result when looking at all cases. Furthermore, most encounters goes through the frontal area thereby having the highest number of updates of *PI*. Fig. 9 illustrates that the database quickly starts to adapt to the new environment, when the test person changes behavior to no interaction after the first 18 encounters.

By coupling the CBR system with navigation, the result is an adaptive robot behavior respecting the personal zones depending on the person's willingness to interact - a step forward from previous studies [15].

VI. Conclusion

In this paper, we have described an adaptive system for natural interaction between mobile robots and humans. The system forms a basis for human aware robot navigation respecting the person's social spaces.

Validation of the system has been conducted through two experiments in a real world setting. The first test shows that the Case Based Reasoning (CBR) system gradually learns from interaction experience. The experiment also shows how motion patterns from different people can be stored and generalized in order to predict the outcome of a new human-robot encounter.

Second experiment shows how the estimated outcome of the interaction adapts to changes of the behavior of a test person. It is illustrated how the same motion pattern can be interpreted differently after a period of training.

An interesting prospect for future work is elaborations of the CBR system, e.g. doing experiments with a variable learning rate and additional features in the database.

The presented system is a step forward in creating social intelligent robots, capable of navigating in an everyday environment and interacting with human-beings by understanding their interest and intention. In a long perspective, the results could be applied in service or assistive robots in e.g. health care systems.

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