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An Adaptive Game Algorithm for an Autonomous, Mobile Robot - A Real World Study with Elderly Users

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Abstract— **This paper presents a field study of a physical ball game for elderly based on an autonomous, mobile robot. The game algorithm is based on Case Based Reasoning and adjusts the game challenge to the player's mobility skills by registering the spatio-temporal behaviour of the player using an on board laser scanner. We have investigated the adaptiveness of the game algorithm in an open-ended environment with older adults using different assistive tools and playing in at a rehabilitation center. The study shows that the robot operates robustly in the real world and that the game algorithm adjusts the challenge to different players, but fails when players show non-standard behaviour.**

I. INTRODUCTION

Based on the demographic development in most western countries, it has been predicted that the number of people with mental and/or physical disabilities will increase while the amount of people to take care of them will decrease [1]. Games based on electronic devices hold a significant promise for enhancing the lives of seniors, potentially improving their mental and physical well-being, enhancing their social connectedness, and generally offering an enjoyable way of spending time [2]. Games linked to physical activity seems especially promising, as mental and physical health can be improved through a small amount of physical exercises [3]. Examples include the use of Nintendo Wii as a way to increase physical activity among older adults [4]. Interfaces and games for many video consoles are targeted at children, and have been reported to cause problems for older adults [5]. A natural extension is to explore if the physical and tangible nature of an autonomous, mobile robot can catalyse physical interaction and potentially be used as a rehabilitation device.

Fasola describes the design and implementation of a socially assistive mobile robot that monitors and motivates a user during a seated arm exercise scenario [6]. In [7], a robot that provides motivation and support for cardiac patients who must perform painful breathing exercises is described. In [8] we have investigated a related game for elderly, and the studies revealed a low degree of rejection and showed how the game potentially could be used to train e.g. the postural control of elderly.

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In this paper, we investigate an adaptive game algorithm for an autonomous mobile robot operating in an open-ended environment in order to facilitate physical movement of the user.

The game is a single player pursuit and evasion game and the goal for the player is to try to hand over a ball to the robot while the robot should try to avoid receiving the ball. According to the theory of Flow [9], successful games are characterized by a correspondence between the skills of the player and the challenge of the game. In this paper, player skill is inferred from the level of mobility, i.e. the ability for a player to move around freely. This ability is estimated using spatio-temporal information from laser scanner images, and the game challenge is continuously adapted by adjusting the robot's navigation pattern based on an adaptive potential field. The goal is to investigate the robustness of the robot game, i.e. whether the adaptive game algorithm based on case-based reasoning adjusts the challenge in an open-ended environment with elderly players who potentially use different assistive tools.

The scope of the paper is on the technical functionality, i.e. the robustness of the implementation based on observation and the inner variables of the game algorithm. Measuring the subjective player response or the physiological benefits of playing the game has been described in another paper [8]. First we describe how the player skill is associated with the spatio-temporal behaviour of the player. Secondly we describe how the algorithm can learn from player behaviour and adapt the challenge of the game by changing the robot's navigation patterns. Finally we describe how the game is evaluated by elderly users based on experimental work at a rehabilitation center for older adults.

II. THE ROBOT PLATFORM

The robotic platform which has been used is shown in Figure 1. The platform has been developed at Aalborg University based on a commercial platform from FESTO equipped with an URG-04LX line scan laser placed $35cm$ above ground level, scanning 220 degrees in front of the robot. A contact is placed in a basket just below the robot's head so the robot can detect when a ball is handed over to it. To detect persons, the robot relies on the scans from the laser range finder using the leg detection algorithm presented in [10]. Just above ground level, 6 infra-red sensors are placed which makes the robot stop when it moves too close to a wall or an obstacle.

The robot platform is equipped with a head having 126 red diodes (LEDs) which enables it to express different emotions

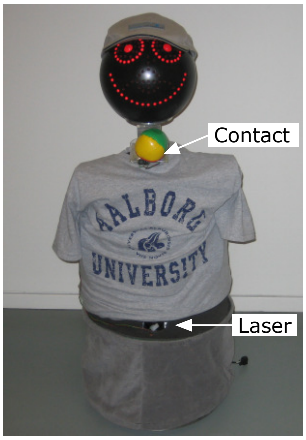


Fig. 1: The modified FESTO Robotino robotic platform.

(a) Confused (b) Neutral (c) Happy (d) Sad

Fig. 2: Using the LED face, the robot is able to express four emotional expressions: confused, neutral, happy and sad. The robot randomly blinks its eyes independent of its expression.

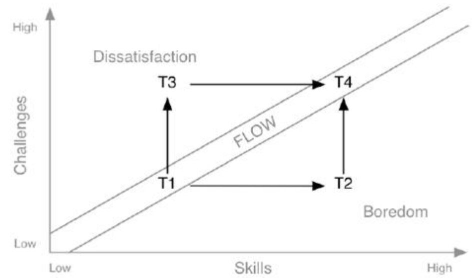


Fig. 3: Illustration of the relation between skill and challenge [9]. In state T1 and T4, there is a balance between skill and challenge and the player is in the state of flow. In state T2 and T3 there is no balance, and the player is either bored or frustrated, correspondingly

(see Figure 1). The robot's face serves as interface to let the player know, when the game changes state. The design of the face was originally inspired by the emotion icons (emoticons) known from e.g. web forums representing facial expressions. A list of emoticons images has been used as a design guideline to indicate the proportion between eyes and mouth. However, the design of the face has not been an academic process and evaluation of the physical design of the robot is outside scope of the paper. Since the experiments were conducted around Christmas, the robot was dressed as Santa Claus.

A. *Player Skill Indication (*PSI*)*

The implemented game is a single player pursuit and evasion game in which the goal for the player is to try to hand over a ball to the robot while the robot tries to avoid receiving the ball. Ideally, the player should be in the state of flow while playing - a feeling characterized by great absorption and engagement as proposed by Cskszentmihly [9]. As illustrated in Figure 3, flow cannot occur if the task is too easy or too difficult.

Player skill is inferred from the level of mobility, i.e. the ability to move freely in two dimensions. In order for the robot to adapt the game challenge to the individual player, is should therefore have an estimate of the player's mobility. This estimate is derived on the basis of the spatio-temporal behaviour patterns of the person, i.e. how the person moves physically in relation to the robot. In order to ensure robustness, we rely on position and pose although more advanced features could be incorporated, e.g. gesture, gaze or even voice.

The skill of a player is annotated using the parameter Player Skill Indication (*PSI*). $PSI \in [0;1]$ is a fuzzy predicate, which represents what the robot believes is the skill of the current player. When $PSI \approx 1$, the robot believes the player is skilled, i.e. that the player is likely to complete a game within a fixed evaluation period L_1. When *PSI* is close or equal to 0, the robot thinks the player is less skilled, and thereby less likely to complete the game within the time L_1.

The behaviour of the player is evaluated through a continuous registration of the players position and orientation of the body, which is inferred from 2D laser range measurements as explained in [11]. The robot relies on the scans from the laser range finder using the leg detection algorithm presented in [10] which has been further supported by a Kalman filter for tracking and estimation of the person pose [11]. The leg detection algorithm is capable of detecting multiple persons in parallel. However, as this is a single player game the closest person is selected.

B. *Learning using Case Based Reasoning (CBR)*

To incorporate the ability to adapt to the behaviour pattern of the player, we have selected to use Case Based Reasoning (CBR). CBR allows recalling and interpreting past experiences, as well as generating new cases to represent knowledge from new experiences [12]. CBR has been proven successful solving spatial-temporal problems in robotics in [13] and is characterized by its transparency and adaptiveness, making it well suited for the purpose. At the highest level of generality, a general CBR cycle may be described by the following four processes:

- Retrieve the most similar case or cases
- Reuse the information and knowledge in that case to solve the problem
- Revise the proposed solution
- Retain the parts of this experience likely to be useful for future problem solving

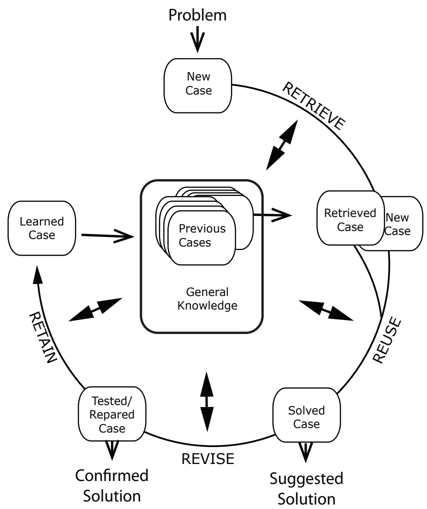


Fig. 4: Illustration of the CBR cycle.

As illustrated in Figure 4, a new problem is solved by retrieving one or more previously experienced cases, reusing the case in one way or another, revising the solution based on reusing a previous case, and retaining the new experience by incorporating it into the existing knowledge-base (case-base) [14].

The CBR system has been implemented using a database which hold cases representing the spatio-temporal data of each player. A case is a representation of a distinct set of features of the behaviour, namely:

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.
PSI, is the value estimated by the CBR system.
Person ID, is an identifier of the interacting person.

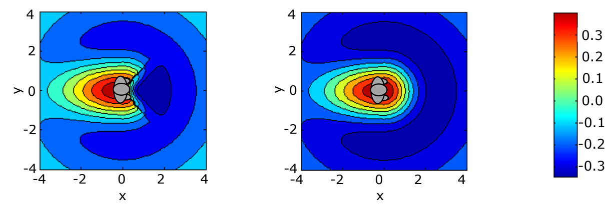
The database does not hold any explicit information about context or the environment in which the game is played. The features **x**, **y** and θ are all stored in a precision which facilitates match-making when performing database queries.

The starting point of the CBR system is an empty database holding no a priori knowledge about player behaviour. While a person plays with the robot, cases are created for each 0.1 second. Because the robot continuously revises the database throughout a game, the system gradually learns how to decode player behaviour into *PSI* values between 0 and 1.

C. The Navigation System

The challenge of the game is automatically adapted by adjusting the navigation pattern of the robot with respect to the parameter *PSI*. The navigation system is modelled by introducing a person centred potential field which has been described in detail in [15], [11] and is briefly summarized here. The potential field is calculated by the weighted sum of four Gaussian distributions of which one is negated, and the covariance of the distributions are used to adapt the potential field according to *PSI*.

When a player is considered to be unskilled (*PSI*=0), the robot will locate itself in the space right in front of the player in a distance of 45 cm, making it relative easy for the player to hand the ball back (see Fig. 5). On the other hand, when a player is considered to be skilled ($PSI = 1$), the robot will end up at the lowest part of the potential function, approximately 2 meters in front of the person using the method of steepest descent. This makes it more difficult for the player to hand the ball back, as he/she has to move relative fast towards the robot which constantly will try to avoid the player.



(a) PSI=0. Unskilled player (b) PSI=1. Skilled player (c) Scale

Fig. 5: The potential field as a function of *PSI*. Using the method of steepest descent, the robot seeks towards the dark blue area and avoids the red area.

D. Control of the Robot

Controlling the robot is done using the programming framework Player which was installed on the platform. The robot game uses the behaviour scheme in Fig. 6 and can be in the following 4 states.

- Evaluation. This is the central state of the game, in which the robot navigates around the player in accordance to the estimated skill (*PSI*) of the player. Revision of the database takes place every time an evaluation period L_1 has elapsed or when the ball has been handed back. In the latter case, the game is complete and the robot will go to the state Avoid and thereafter Roaming.
- Roaming. If no player is detected, the robot should search for a player by moving randomly until a person is spotted.
- Approach. When a player is detected, the robot invites to play a game by approaching the player from the front.
- Avoid. In this state, the robot moves quickly backwards away from the player while turning around its own axis for L_2 seconds. The state is reached when a player picks up or hands back a ball, and the behaviour communicates to the player that a game starts or stops respectively.

The adaptive navigation according to *PSI* happens when the robot is in the evaluation state, while the states Roaming, Approach and Avoid are static navigation patterns working

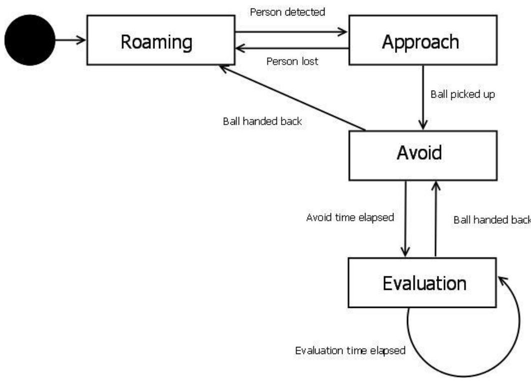


Fig. 6: State diagram of the adaptive robot game.

ID	Sex	Age	Assistive tools	# of Games	# of stored cases	Avg. Time (s)	Avg. PSI
P1	F	82	No	10	89	31	0.53
P2	F	86	No	10	30	17	0.71
P3	F	71	Crutch	10	133	29	0.37
P4	F	85	Wheelchair	3	114	51	0.15
P5	M	86	No	3	119	41	0.14
P6	M	90	Walker	3	100	58	0.11

TABLE I: Summary of player attributes. The total number of games played, the total number of stored cases, the average play duration and the average *PSI* value

independently of *PSI*. The Roaming and Approach behaviour have been implemented for the robot to be able to search for a player and initiate a game, while the Avoid behaviour has been implemented to signal to the player when a game has started and when it has finished. For each state, the robot changes its facial expression reflecting the current state. A more detailed outline of the algorithm can be found in [16].

III. Design of the study

The field study took place in a real world scenario at a rehabilitation facility for elderly citizens located at a nursing home. There was a total of 6 participants (labeled P1 through P6 in Table I). Four out of 6 participants were female. Three lived in their own home and attended the rehabilitation facility due to different mobility problems, while the other three were permanent residents of the nursing home. The average age was 83.3 years and three out of 6 used an assistive tool. None of the participants had technical background. A physiotherapist working at the facility was monitoring the elderly playing with the robot and the session was also video recorded for later analysis.

The procedure of the experiment was as follows: First there was a general introduction of the experiment, then a demonstration of the robot and afterwards the players were asked to play one at the time. Finally there was a debriefing about the experiment. The study took a total of 4 hours. The evaluation time was set to $T_1 = 3s$, while the avoid time was set to $T_2 = 5.5s$, making the robot move backwards and turn around showing the back to the participant every time a ball had been picked up or handed back.

Fig. 7: A participant using a wheelchair playing a game with the robot, trying to hand back a ball while the robot moves.

IV. Results

As can be seen in Table I, the first three participants completed a total of 10 games but player P4 complained about pain due to arthritis caused by lifting the ball after 3 games. To make sure that no one was harmed by the experiment, is was decided to reduce the number of games for the remaining participants.

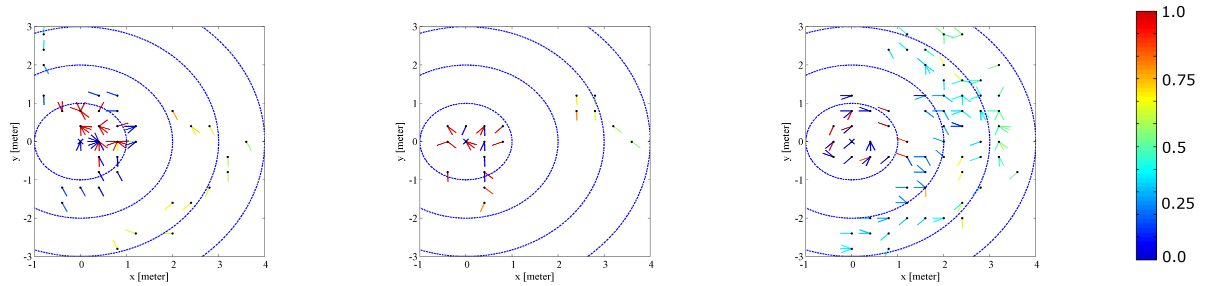
As explained earlier, the starting point of the CBR system is an empty database. As a participant starts to play, his movements get registered by the robot and the database gradually gets filled with cases.

The stored cases in the database for each player are illustrated by four-dimensional plots in Fig. 8 and Fig. 9. The robot is centred in 0,0 and the first two dimensions in the plot illustrate the position of the person in the robot coordinate frame. At each position, the pose of the person is illustrated by a vector. The colour of the vector denotes the value of *PSI*. Blue colour represents that the person is not skilled, while the red colour represents that the person is skilled, i.e. $PI = 0$ and $PI = 1$ correspondingly. A green vector represents the default value $PI = 0.5$.

Figure 10 represents the evolution of the database for player P1 and P4 which have been subjectively selected for the purpose of illustration. The figure plots the average *PSI* for all cases which has been calculated for every time a revision of the database has been executed. Initially *PSI* = 0.5 for both players, but as player P1 starts to play, the *PSI* value quickly falls to 0.24 (after 38 revisions) and after 187 revisions it has fallen to a minimum of *PSI* = 0.16. As player P1 keeps playing, *PSI* grows and ends in 0.53 which is also the maximum average *PSI* value for P1. When player P4 starts to play, the average *PSI* value falls to 0.05 after 38 revisions. Then the average value slowly increases ending with *PSI* = 0.15 after 400 revisions.

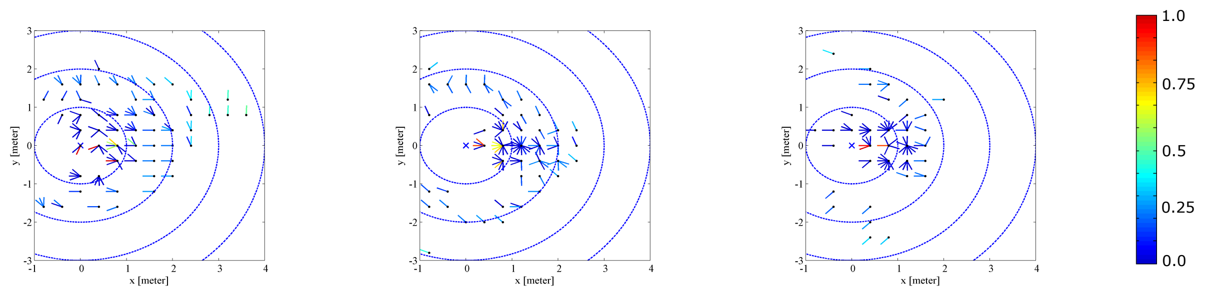
V. Discussion

A general pattern of all plots in Figure 8 and Figure 9, is that the vectors are gradually turning from either red or blue to green as distance to the robot increases. This is expected, as the weight of the update is a function of distance, making the cases more stable around 0.5 as distance increases. Also



(a) Stored cases for player P1 (b) Stored cases for player P2 (c) Stored cases for player P3 (d) *PSI*

Fig. 8: The figures show the values stored in the CBR system after completion of player P1, P2 and P3. 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 player in the robot coordinate frame. The direction of the movement of the player is represented by a vector, and the *PSI* value is indicated by the color range.



(a) Stored cases for player P4 (b) Stored cases for player P5 (c) Stored cases for player P6 (d) *PSI*

Fig. 9: The figures show the values stored in the CBR system after completion of player P4, P5 and P6. The robot is located in the origin (0,0). Each dot represents a position of the player and the direction of the movement is represented by a vector. The *PSI* value is indicated by the colour range.

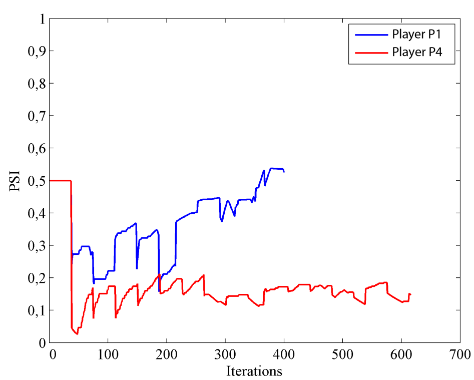


Fig. 10: Illustration of how database evolves. The figure shows the average *PSI* for all cases for player P1 and P4 as a function of the revision of the database.

more updates to the *PSI* happen close to the robot as for most players, the physical behaviour happens close to the robot. Consistent behaviour makes adaptation go faster as more updates of the existing cases occurs, whereas new behaviour patterns will tend to make the average *PSI* move towards 0.5 as all new cases will be added with this default value.

Table I shows the number of stored cases per participant and the average time to complete a game. Although the player with the lowest average playtime (P2 with $t = 17s$) also has the lowest number of stored cases ($n = 30$), there does not seem to be any correspondence between the average time playtime and the number of stored cases, i.e. P3 who has the second fastest playtime ($t = 29s$) has the highest number of stored cases ($n = 133$). The players who only played 3 games, have a higher number of stored cases in average than the players who plays 10 games. This is surprising, but is probably due to fact the latter group of players on average moved slower making the robot capable of registering more cases.

In Table I, it can be seen that the player having the maximum average playtime is P6 who uses a walker ($t = 58s$), whereas the fastest player is P2 who does not use assistive tools ($t = 17s$). The table also shows that while P6 has the lowest ($PSI = 0.11$), P2 has the highest ($PSI = 0.71$). In other words, the fastest player has the highest estimated skill *PSI* while the slowest has the lowest.

Due to the nature of the game algorithm it is reasonable that there is some kind of correspondence between the average *PSI* and the average playing time, as more negative revisions of *PSI* happens the longer time is spent moving around the robot before the ball is handed back to the robot.

It can be discussed if the average *PSI* value is an adequate representation of a player's skill, as it is calculated on the basis of a spatio-temporal database. In theory, this means that a player can have a high average *PSI* for one behaviour pattern and a low average *PSI* for another in the same game, resulting in an average *PSI* in between the two. For the sake of simplicity, the average *PSI* is used here as an indicator of the player's skill, but it should not stand alone and has to been seen in relation to other data describing the player behaviour.

Looking at Table I, it seems surprising that P1 spends more time completing the games than P3 because P3 uses a crutch whereas P1 does not use any assistive tool. This might be due to the fact that P1 was the first participant playing the game and seemed insecure of how the game worked. It is also surprising that P5 is slower in average than P3 who uses a crutch as P5 did not use an assistive tool and seemed very mobile. However, it was observed that P5 had a very unique play style. He decided to spend relative long time to hand the ball back as he apparently liked to tease the robot and see its reactions. As a consequence, the *PSI* for player P5 (=0.14) is on the same level as e.g. P4 (=0.15) and P6 (=0.11), although the latter two players were using a wheelchair and a walker. This illustrates an inherent problem of dynamic skill level adjustment, as exploratory and non-standard behaviour has to be identified and filtered out.

Figure 10 starts with *PSI* = 0.5 for both players as the database starts being empty, meaning that the robot has no experience and hence use the default *PSI* value which is 0.5. When comparing the two players, it is clear that the system believes that player P1 has higher skills as *PSI* ends at a higher level than for player P4. This makes sense as player P1 did not use assistive tools whereas player P4 was using a wheelchair. There seem to be more variation in the estimated skills of player P1 compared to player P4. This might be due to the fact that player P1 seemed insecure of how the game worked in the beginning.

VI. Conclusion

In this paper, we have presented a field study of an adaptive game algorithm for an autonomous, mobile robot. The game is a pursuit and evasion game which can adjust the challenge of the game to the mobility skills of the player. Skill is represented using the variable *PSI* and is estimated from spatio-temporal registrations of player behaviour and adaptation is based on case-bases reasoning. The game has been evaluated in a real-world environment by older adults in a rehabilitation centre.

The results show that the implemented game algorithm works robustly in an open-ended environment when the robot plays with older adults who potentially use different assistive tools. A fuzzy estimate of player skill can be derived based on the spatio-temporal behaviour of the players using a laser range finder as input. Although the system adapts the game challenge to the behaviour of the individual player it fails when participants show non-standard behaviour. In future robot based games, incorporating more complex sensors technologies might mitigate this but more research is needed.

VII. Ethical considerations

The study was approved by The Danish Data Protection Agency. Participants consented to video-recording and were informed about the study orally and in writing. Participants were explained the purpose of the investigation, that participation was voluntary and that they might withdraw at any time; they were assured that any information given would be treated in confidence and reported anonymously.

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