Pro-active positioning of a social robot intervening upon behavioral disturbances of persons with dementia in a smart nursing home

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Abstract

Behavioral disturbances of persons with dementia residing in a nursing home impose a significant burden on other residents and on the care staff. A social robot can provide an adequate technological support tool for the caregivers by approaching a resident that exhibits a behavioral disturbance. In this paper, we focus on how to position the robot in the nursing home, taking into account the profile and location of the residents. We minimize the time between the detection of a behavioral disturbance and the robot having arrived near the resident and starting an interaction scenario. Our algorithm is evaluated using realistic data that was collected during 3 months in two Belgian nursing homes.

Keywords: personalized care, smart environments, Internet-of-Robotic-Things, social robotics

1. Introduction

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Dementia is characterized by a progressive decrease of ³² cognitive capabilities that affects memory, thinking and ³³ social abilities severely enough to interfere with daily func- ³⁴ tioning. As age is one of the strongest known risk factors ³⁵ for dementia, the worldwide cost of dementia care services ³⁶ is projected to grow significantly with the aging popula- ³⁷ tion (World Health Organization, 2018; Harper, 2014). ³⁸

Ambient assisted living technology can reduce costs by ³⁹ extending the period in which older adults can stay inde- ⁴⁰ pendent in their home (Demir et al., 2017). Over time, the ⁴¹ care for a person with dementia often becomes too com- ⁴² plex to be organized in the home environment, and at a ⁴³ certain point the person needs to be placed in a nursing ⁴⁴ home with guaranteed supervision and specialized facili- ⁴⁵ ties (Mller et al., 2017).

The corollary of these societal and technological evolutions is that the care needs of the average nursing home ⁴⁸
resident are becoming more complex and that the demand ⁴⁹
by the staff for technological support tools is increasing ⁵⁰
accordingly (OSullivan et al., 2018). Behavioral distur- ⁵¹
bances (BD) are one of the most prominent manifestations ⁵²
of dementia, exhibited by a majority of the persons with ⁵³
moderate to severe dementia living in nursing homes (De- ⁵⁴
sai et al., 2012; Husebo et al., 2011). BD can take various ⁵⁵
forms, including mood disorders, wandering and verbal or ⁵⁶
physical aggression. These BDs are an important inhibitor ⁵⁷
of stress to other residents as well as to caregivers (Hazel- ⁵⁸
hof et al., 2016).

To manage these BDs, one can use pharmacological or non-pharmacological interventions. Pharamacological interventions are used only in acute situations since these treatments do not address the underlying psychosocial reasons and may have adverse side effects (Sadowsky and Galvin, 2012). Many different non-pharmacological therapies are designed to resolve specific BDs by interacting with the residents and without the harmful effects of medical interventions (de Oliveira et al., 2015). Robot-Assisted Therapies are one particular form of non-pharmacological therapy. Many recent studies investigated the effects of various social robots on persons with dementia, such as the robot seal PARO or the humanoid Nao (Sabanovic et al., 2013; Jøranson et al., 2015; Wada et al., 2005; Valent Soler et al., 2015; Inoue et al., 2014). Even with relatively simple interactions such as storytelling, singing a song or performing a dance, a positive effect on the neuropsychiatric symptoms is reported. However, these robots only interact in a preprogrammed manner and it is often too time consuming for the staff to program new therapy sessions on the robot.

Our aim is to evolve the role of a social humanoid robot in the caregiving workflow from a tool that is manually controlled during therapy sessions to an autonomously functioning technological support tool. In particular, when a BD manifestation is detected from sensors installed in the nursing home or from wearables worn by the residents, the robot should drive to the resident, and generate an audio-visual stimulus to temporarily distract the resident and possibly alert the staff if the BD manifestation is not stopped.

A key component of such a system - and the main contribution of this paper - is a control algorithm that pro-

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actively positions a social robot in a nursing home in order₁₁₉ to minimize the Time-To-Intervention (TTI) for a maximum number of BD manifestations. We define the TTI as the time elapsed between the detection of a BD from₁₂₀ the sensor data and the robot having approached the resident close enough to start an intervention. We evaluate this algorithm with simulations based on realistic datasets annotated by the staff of closed dementia wards in two 124 nursing homes in Belgium. Our use case imposes the following specific requirements:

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- Single robot Social robots are an expensive invest-127
 ment for nursing homes which are, in Belgium as 128
 well in many other countries, under financial pressure. 129
 The controller algorithm was thus primarily designed 130
 for a single robot, leaving extensions to multi-robot 131
 deployments for future work.
- 2. Location priority Although some patterns can be₁₃₃ observed in the daily displacements of a resident, the₁₃₄ occurrence of a BD is a stochastic process related to₁₃₅ the individual and not to a spatial position such as₁₃₆ a common room or the bed room. These patterns₁₃₇ change over time, e.g. when a new resident arrives af-₁₃₈ ter the decease of a resident (caregivers report typical₁₃₉ stays of 9-15 months), or if the frequency of BDs of a₁₄₀ resident increases as dementia progresses. Therefore,₁₄₁ the robot should adapt its position to the actual loca-₁₄₂ tion of the residents, weighted for the statistical BD₁₄₃ risk profile of each resident.
- 3. Trajectory As BD events are detected using wear-145 ables or sensors, the main design goal for the robot's 146 trajectory in the nursing home is to arrive as fast as 147 possible to a resident if such an event occurs not to 148 patrol and detect as much BDs as possible. If no resident moves significantly a situation not uncommon 150 in a nursing home the optimal robot position does 151 not change and the robot can stay idle.
- 4. Finite duration BD events have a finite duration, $_{153}$ meaning that a BD can only be alleviated if a robot $_{154}$ arrives within a fixed duration after the onset of a BD. $_{155}$
- 5. Energy management Since the system is intended as 156 a support tool in the caregiving workflow, the amount 157 of actions required from the caregivers must be as minimal as possible. The robot should timely move 159 itself to a charger location. Preferably, charging cycles are scheduled when fewer BD events are expected.

The rest of this paper is structured as follows. In sec-162 tion 2, we relate existing studies on robot positioning al-163 gorithms to the specific requirements imposed by BD in-164 terventions. In section 3 we situate this positioning algo-165 rithm in a broader cyber-physical framework that contains 166 components for BD detection, positioning and navigation. 167 In section 4, we explain our control algorithm that deter-168 mines the position and charging times of the robot. In 169 section 5, we evaluate the performance of our pro-active 170 position control algorithm. We conclude the paper in sec-171 tion 6.

2. Related work

Continuous surveillance of a target environment by a robot has a wide range of applications such as property surveillance, environment monitoring in disaster sites and ecological monitoring (for an extensive review, see e.g. Nigam (2014)). Our studied problem of a robot positioning itself nearby locations of interest relates to robotic surveillance. In this section, we evaluate existing work on the requirements that were listed in section 1. A summary can be found in Table 1.

In many of the works in this domain, the robot cycles through a predetermined sequence of locations. The aim is to balance dwell time, i.e. time spent at each location, with the time between two visits of the same location, see e.g. Smith et al. (2012), Yu et al. (2017)). For our use case, fixed patrolling circuits are less efficient since the trajectories followed by residents may vary from day to day. Yu et al. (2015) and Baykal et al. (2016) study a problem where events are generated according to a location-specific Poisson process. The trajectory and dwell times of a single robot are optimized to register as much events as possible. The events considered in these works are instantaneous: if the robot is not at the location when an event occurs, it is completely missed by the robot. The goal of our control algorithm is however to maximize the number of BDs alleviated (i.e. robot arrives no longer than a time T after the onset of a BD) and not to maximize the number of BD events detected, since BD detection is performed by sensors and wearables.

Battery management is often accounted for in terms of a constraint, ensuring that the robot arrives at a charging point (just) before running out of battery. For instance, Mersheeva and Friedrich (2015) calculate trajectories for a set of unmanned aerial vehicles where batteries can only be replaced at a limited set of locations. Rather than maximizing the length of a single trajectory between subsequent charging cycles, we let the robot charge its battery in idle times such that it can alleviate more BDs whenever they do occur.

In Tran et al. (2017), three different technologies are compared to solve the planning and scheduling problem of deploying multiple robots in a nursing home environment. Multiple robots need to jointly fulfill a set of tele-presence sessions, reminding residents about the upcoming Bingo activity as well as leading the Bingo activity. At the beginning of each day, a new task schedule is generated for each robot. Our position control algorithm is not designed for such deadline and location-constrained announcement and interaction tasks. Instead, we position the robot nearby residents so that the robot can quickly reach them if a resident starts exhibiting a BD. Finding an robot schedule for the combination of pre-scheduled and stochastically arriving interaction tasks is an interesting topic for future research.

| | Single or multi-agent | Trajectory | $Energy\\management$ | Location priority | Event type |
|-----------------------------------|-----------------------|---|--|---|-----------------|
| Smith et al. (2012) | Multi | Predetermined static cycle | None | Dwell times based on accumulation function | None |
| Mersheeva and Friedrich (2015) | Multi | Sequence over landmarks, with replacement of batteries at base stations | Charge when critically low | Predetermined stationary location priorities | None |
| Yu et al. (2015) | Single | Periodically updated sequence over landmarks, without revisits | None | Rate of events (stationary) | Instantaneous |
| Baykal et al. (2016) | Single | Periodically updated sequence over landmarks, with possible revisits | None | Rate of events (non-stationary) | Instantaneous |
| Tran et al. (2017) | Multi | Planned based on resident day schedule | Charge times are included in plan | Fixed day schedule for resident | None |
| Yu et al. (2017) | Single | Fixed sequence over landmarks, no revisits | None | Time since last visit and dwell time | None |
| Ours | Single | Dynamic positioning on grid | Charge in idle times or when necessary | Risk-weighted person tracking | Finite duration |

Table 1: Comparison of the proposed framework with current state of the art on the requirements for BD intervention introduced in section 1.

3. Background

The positioning algorithm is part of a complete framework for personalized interventions of social robots, developed in the WONDER project¹. In this section, we delineate the responsibilities of the positioning algorithm in the framework and briefly discuss the other building blocks that have been realized in the project.

Our system was designed in co-creation with the staff of closed dementia wards in two nursing homes. In such a ward, residents have their private bedroom while meals and leisure activities are organized in common rooms. For reasons of personal safety, residents cannot leave the ward unaccompanied.

The framework can be seen as a cyber-physical system that receives constant input from sensors and wearables on the residents and that steers a social robot throughout the premises of the nursing home: corridors, common rooms and private bedrooms. The conceptual architecture is illustrated in Figure 1.

The data processing block continuously tracks the residents' locations and whether they start exhibiting a behavioral disturbance (BD), e.g. by monitoring sound level to detect yelling or by tracking walking patterns to detect

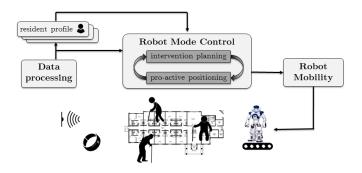


Figure 1: The social robot alternates between a pro-active mode and an intervention mode, based on real-time sensor data as well as historical information. The Robot Mobility block controls navigation through the corridors, common rooms and (private) bedrooms.

 $^{^{1} \}verb|https://www.imec-int.com/en/what-we-offer/| research-portfolio/wonder$

wandering behavior. Such BD detection algorithms have for instance been reported in (Lin et al., 2018; Vuong et al., 2015; Beltrán et al., 2014).

The robot control alternates between a pro-active mode and an intervention mode. In the default pro-active mode, the robot is positioned close to where the most BD are expected in the near future. As we will detail in the rest of this paper, these estimations are based on the combination of historical information on BD occurrences for each resident with real-time location information. For instance, during the night the robot will position itself closer to the bedrooms, while in the afternoon it will be close to a common room where all residents are gathered.

If a BD is detected, the system switches to the intervention mode. The robot drives towards a particular resident to attempt to alleviate the BD by starting an interaction. The success of the robot intervention can be monitored again via the wearables and sensors and if necessary, a caregiver is alerted for further assistance.

3.1. Personalized interactions

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In co-creation with the nursing home staff (Ongenae₂₅₃ et al., 2017), we defined a number of intervention actions₂₅₄ that the robot can perform when in front of a resident:255 asking a question about an important event in his lifetime, 256 reading out a news highlight and playing a song. Both the₂₅₇ style and content of the intervention are tailored to the 258 resident. Style parameters include the language, speak-259 ing volume and approaching distance. The robot can play 260 a favorite song, tell a short story about a topic of interest (e.g a news headline) or elicit a positive memory from 261 the resident's lifetime. All these robot actions, together with profile information, are formally described in an onto logy. Modeling this information in an ontology allows to $_{^{264}}$ incorporate knowledge from other domains, for instance, 265 notions of an elderly's culture that determine the $style_{266}$ of greeting (Bruno et al., 2017) or the way of approach- $_{\scriptscriptstyle 267}$ ing (Truong et al., 2016). By following and interpreting $_{268}$ the links in the ontology, it can be automatically derived which profile information can be used to personalize the $_{270}$ action. The effort of the care staff is limited to inputting some basic profile information about interests, language, etc. This is information that is already captured in today's care practices.

3.2. Mobile platform for the Nao robot

In our study, we used the humanoid Nao robot. The same robot was used in the KSERA project (Torta et al., ²⁷⁵ 2014). The obtained results in a senior center home suggest that the participants did not feel any anxiety during interaction, mostly due to the shape and small size of the robot.

It is important for the robot to move fluently through-²⁸⁰ out the nursing homes. The Nao robot is however a legged²⁸¹ robot that walks too slowly for our needs as it is limited to a speed of roughly 10 cm/s. To enable a more swift movement between locations in the nursing home, a new mobile





Figure 2: Front and backside view of the platform used by the social robot to move efficiently through the nursing home. The robot can autonomously step on and off the platform.

platform has been designed, shown in Figure 2². The platform's mobility is accomplished by continuous track tires which are actuated by two independent motor drivers. We have equipped it with 5 simple sonars as well as a Robo-Peak A1 lidar. The platform has a top speed of 1 m/s making it much more suitable for a nursing home environment. The red color for the front was advised by the nursing home staff as red is the color that is most likely to be noticed by the persons with dementia.

3.3. Study design

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Real sensor data was collected in two nursing homes located in Ghent, Belgium. Although we realized an integrated prototype of the framework in which a robot enters a room and initiates a personalized intervention (see Figure 2), we were not able to organize field trials to validate the positioning algorithm presented in this paper. The main reason is that the newly designed mobile platform was implemented as a proof-of-concept but was not certified for experimenting with humans in real environments. Hence, the experimental validation of the positioning algorithm is based on simulations with real data on BD manifestations in a dementia ward.

4. Robot Position Control

Residents constantly move between their room, the common areas and the corridors in the ward. If a BD is detected from sensor data, the robot will plan a personalized intervention. If no resident is currently exhibiting a BD, we aim to position the robot so as to minimize the *time-to-interaction* (TTI), which we define as the time between the detection of a BD and the robot arriving at the resident's

 $^{^2\}mathrm{A}$ video of the robot driving around can be found at https://vimeo.com/243125775.

Algorithm 1 Control routine

```
while true do
                                                                    318
2:
        if has_to_charge() then
                                                                    319
            navigate_to(\vec{x}_{charger})
 3:
                                                                    320
            wait_until_charged()
 4:
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        else if can_alleviate_bd() then
 5:
                                                                    322
            navigate_to(\vec{x}_{BD})
 6:
                                                                    323
            execute_personalized_interaction()
 7:
                                                                    324
 8:
                                                                    325
            do_proactive_action()
9:
                                                                    326
        end if
10:
                                                                    327
11: end while
                                                                    329
```

current location and start a personalized intervention sce-331 nario. As we will show in section 5.1, our empirical data332 collected in two nursing homes reveals temporal patterns333 in the type of BD exhibited, e.g. there are typically fewer 334 BDs during organized activities or meals. Therefore the 335 control algorithm will constantly steer the robot towards 336 locations in the ward where there is a high probability of a 337 resident exhibiting a BD. Our algorithm is designed such 338 that it can be deployed in any nursing home (e.g. with dif-339 ferent day schedule) or with changing population charac-340 teristics (new residents, progressively declining residents). 341 Lastly, the robot should never run out of out battery so the 342 control algorithm must also decide when the robot should 343 move to a charging station deployed in the nursing home. 344

4.1. Environment model

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We define the nursing home as a two-dimensional grid X wherein our robot as well as all residents are at discretized time t positioned at one of the possible positions $\vec{x} = (x,y) \in X$ on the grid. Example grids of the two nurs-348 ing homes participating to our study are shown in Fig. 3.349 We denote the battery level of the robot at time t as $b(t)^{350}$ (0 < b(t) < 100). There is a single charger placed at 351 location $\vec{x}_{charger} \in X$.

At any moment in time, the robot is either standing³⁵³ idle (on a non-charger position), charging, moving (with a constant speed v) or interacting with a resident. The corresponding depletion of the battery per time step, Δb , is modeled as fractions of a base discharge per timestep c:

$$\Delta b = \begin{cases} c \cdot f_{idle} & \text{if idle} \\ -c \cdot f_{charge} & \text{if charging} \\ c \cdot f_{move} & \text{if moving} \\ c \cdot f_{int} & \text{if interacting,} \end{cases}$$

The actions of the robot are controlled by a continuously running control algorithm, of which the pseudo-code is displayed in Alg. 1. Every iteration of this control algo-358 rithm starts with a check of the current battery level of the 359 robot. The function $has_to_charge()$ (line 2 of Alg. 1) com-360 putes the distance $D(\vec{x}_{robot}, \vec{x}_{charger})$ between the current 361

robot position and the location of the charger and checks if the current battery level is still sufficient for reaching the charger, i.e. if $b(t) > D(\vec{x}_{robot}, \vec{x}_{charger}) \cdot c \cdot f_{move} + B_{min}$, with B_{min} a safety margin.

As distance measure D(x,y) we take the A^* -distance (Hart et al., 1968). If the battery level is not high enough then the robot will immediately go towards the charger. By performing this check we ensure that our robot never runs out of battery, which would require a manual intervention of the staff. Please note that once an robot decides it must charge, it will always fully charge. We have chosen to do this in order to avoid pivoting behavior and shall further motivate this choice after explaining the cost functions in more detail (see section 4.3).

If the robot does not need to charge, the control routine checks if the algorithms analyzing the sensor data report a BD ongoing at one of the residents (line 5 of Alg. 1) and if it can alleviate them depending on the location of the reported BD, the robot's current position and its battery level. It again checks this by computing the power necessary to (i) travel towards the location of the ongoing BD, (ii) alleviate the ongoing BD and (iii) travel from the BD location to the charger. If the robot cannot alleviate the BD due to energy constraints, the ongoing BD will be ignored.

If there are no ongoing BDs and the robot has sufficient battery, we execute a cost-based optimal control problem (line 9 of Alg. 1) to optimize the robot position (in terms of TTI). The internals are detailed in the next section.

4.2. Pro-active action control

In pro-active mode, the robot can take five possible actions $a \in \mathcal{A}$: moving one grid cell up/down/left/right or stay on the current location (idle). The optimal anticipative action for the robot depends on the relative position of the robot towards the charger and towards all residents, the probability of all residents to exhibit a BD in the near future, and the actual battery level b(t).

We define our state space as:

$$S = \{s(t) = (\vec{x}_{robot}, \vec{x}_{resident}, b(t), t) | \vec{x}_{robot} \in X,$$
$$\vec{x}_{resident} \in X, b \in [0, 100] \}$$
(1)

We consider movement of our robot to be noiseless and therefore the state transitions $s \to s'$ are deterministic. The optimal action a^* is then determined as the action for which the cost of the resulting state s' is lowest:

$$a^* = \arg\min_{a \in A} \left[C_{env}(s', a) + C_{BD}(s', a) + C_{bat}(s', a) \right]$$
 (2)

The cost terms in Eq. (2) are designed to strike a balance between the Time-To-Interception (TTI) and not running out-of-battery. These cost functions are explained in more detail below.

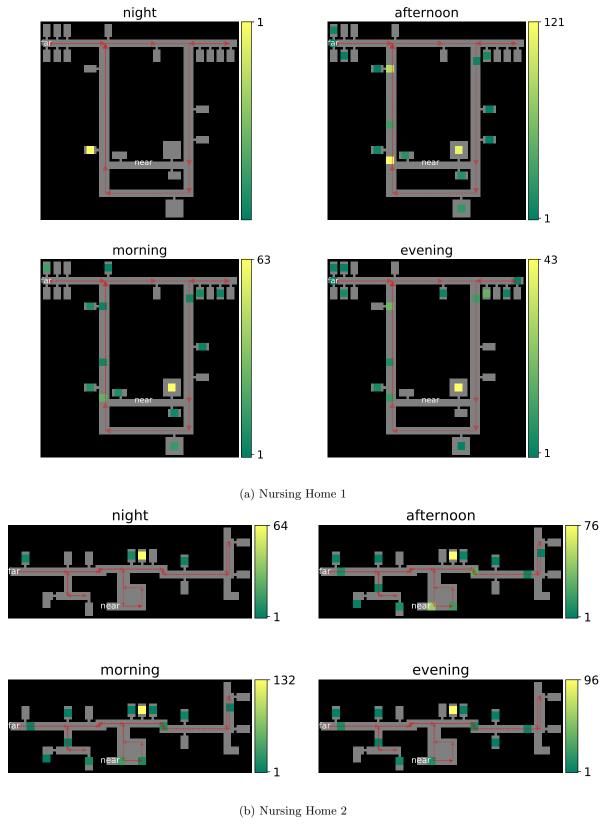


Figure 3: Heatmap of the locations where BDs are taking place in the nursing homes. Accessible areas are coloured gray while inaccessible ones are black. Small rooms on the outer rim of the grids are patient rooms while large rooms indicate common rooms. The plans are reduced versions of the original floor plans because rooms of patients for which no informed consent of the patient was obtained are also marked as inaccessible. Colours indicate the number of behavioral disturbances collected over 100 days for nursing home 1 and 135 days for nursing home 2. The red dotted line is the patrolling path for the patrolling baseline. The night is defined between 22:00 and 06:00, the morning between 06:00 and 12:00, the afternoon between 12:00 and 18:00 and the evening between 18:00 and 22:00.

4.2.1. Environment cost

The cost linked with the environment, C_{env} is intro-³⁹⁸ duced to ensure that our robot does not take an impossible³⁹⁹ action by for example walking into a wall.

$$C_{env}(\vec{x}) = \begin{cases} \infty & \text{if } \vec{x} \text{ is infeasible/occupied} \\ 0 & \text{otherwise} \end{cases}$$
 (3)

4.2.2. Battery cost

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Each action draws a certain amount of energy from the battery, which is accounted for by assigning a cost to each action. Furthermore the battery cost C_{bat} contains a linear cost for the distance to the charger. This part ensures that if the other terms in the total cost function are zero then our robot is steered towards the charger. The cost term C_{bat} thus becomes:

$$C_{bat}(s, a) = C_{charger}(\vec{x}_{robot}) + C_{action}(a) \tag{4}$$

where $C_{charger}(\vec{x}_{robot}) = D(\vec{x}_{robot}, \vec{x}_{charger})$

$$\text{and} \ \ C_{action}(a) = \begin{cases} c \cdot f_{idle} & \text{if } a = \text{``idle''} \\ c \cdot f_{move} & \text{if } a = \text{``up/down/left/right''} \end{cases}_{\text{406}}^{\text{408}}$$

$$c \cdot f_{int} & \text{if } a = \text{``interact''}, \qquad \text{407}$$

This cost term competes with the cost C_{BD} reflecting⁴⁰⁹ the anticipated BDs. The charger will thus become an⁴¹⁰ attractive position for the robot if very few BDs are anti-⁴¹¹ cipated in the near future.

4.2.3. BD anticipation cost

At any idle moment, and if the battery level is sufficient, the robot should position itself close to the location where the robot should position itself close to the location where the analy residents are gathered that have a high probability of exhibiting a BD in the near future. We therefore assume the availability of a predictor function $\mu\left(r,t,t_{\mu}\right)$ which returns the probability that resident r will exhibit one or more BDs in the interval $[t,t+t_{\mu}]$, with t the current time and t_{μ} a lookahead-time that indicates how far our robot should look into the future for anticipating BDs. This predictor function can be based on advanced machine learnable good results with a simple daily updated historical profile to the cost term for BD anticipation is then given by weighing the distance between the robot and all residents with the predicted BD likelihood for that resident:

$$C_{BD}(s,a) = \sum_{\mathbf{r}} \mu(\mathbf{r}, t, t_{\mu}) D^{2}(\vec{x}_{robot}, \vec{x}_{resident}) \qquad (5)_{43}^{43}$$

In Eq. (5), D is again the A^* -distance measure on a grid.⁴³³ The distance is squared such that decreasing the distance.⁴³⁴ from the robot to a location with future predicted BDs.⁴³⁵ decreases this cost term more than how C_{bat} is reduced by.⁴³⁶ moving the robot towards the charger. This ensures that.⁴³⁷

if there are residents with predicted BDs between t and $t+t_{\mu}$ the robot is steered towards them in favor of going to the charger.

We scale the lookahead-time t_{μ} with the battery level b such that the time window decreases in size as the battery level decreases. Resulting from this comes the intuitive result that steering towards the charger (due to the linear battery cost) becomes more attractive as the battery decreases since the number of expected BDs (and thus the cost term C_{BD}) also decreases due to a smaller time window. Specifically, the time window is set equal to

$$t_{\mu}(s) = \max\left(0, t_{depl}(b) - \hat{t}(s)\right) \tag{6}$$

where

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$$\hat{t}(s) = t_{\vec{x} \to \vec{x}_{charger}}(s) + t_{fullcharge}(b) + t_{alleviateBD}(s)$$

where $t_{depl}(b)$ denotes the time needed for the battery to deplete fully, $t_{\vec{x}_{robot} \to \vec{x}_{charger}}$ the time needed to travel to the charger from the current position, $t_{fullcharge}$ the time needed to fully charge from the current battery level and $t_{alleviateBD}$ the time needed to (i) travel to the nearest resident, (ii) alleviate a BD at that location and (iii) travel from that location to the charger. Intuitively, Eq. (6) reflects that we should not look for BDs expected in the far future if we have only a limited battery level. In the case where the battery level decreases below a certain point we have $\hat{t} \geq t_{depl}$ and thus $t_{\mu} = 0$ at which the cost C_{BD} vanishes. The battery cost C_{bat} is then minimized by steering the robot towards the charger as desired.

4.3. Avoiding pivoting behavior

The different terms of the cost function try to attract the robot either to the charger or to other positions in the grid. As introduced in section 4.1, the robot always charges to full in case it decides to charge. One might wonder why a robot could not leave the charger to alleviate a BD without being charged to full. Early experimentations showed however that without imposing the constraint to charge to full, the robot might start constantly pivoting between two positions on the grid. Consider for example the case that our robot is at a low battery level. Since its battery level is low, the lookahead-time is small and the predictor functions $\mu(.)$ will indicate a low probability. However, as its battery charges the lookahead time increases accordingly and BDs might be anticipated. Since the battery level has increased by positioning itself on the charger, the robot is steered again towards the expected BD. As soon as the robot leaves the charger position its battery level drops, thus decreasing its lookahead-time again and the anticipated BD might disappear outside of its time window t_{μ} . In this case, the robot again decides to steer towards the charger and the process repeats once its battery level rises again slightly. The result is that our agent will constantly pivot between charging and going towards an optimal location while its battery will reach a certain level. The robot

will only take steps on and off the charger position and 489 will be unable to alleviate any BD. In order to prevent 490 this undesired behavior we have chosen to let the robot 491 always charge to full if it positions itself on the charger 492 while its battery is not fully charged.

5. Evaluation

In this section, we evaluate the control routine that was 497 presented in Alg. 1. We will compare with two baselines: 498

- a reactive controller, called return, that will always⁵⁰⁰ steer the robot to the charger if there is no BD ongo-⁵⁰¹ ing. If there is a BD ongoing (and the robot is not⁵⁰² in an intervention), the controller will always move⁵⁰³ the robot to the resident, unless there is insufficient⁵⁰⁴ battery. Essentially, this comes down to nullifying the⁵⁰⁵ term C_{BD} while keeping the rest of Alg. 1 unmodi-⁵⁰⁶ fied.
- a patrolling controller, called *patrolling*, will make the₅₀₉ robot follow a fixed and predefined path through the₅₁₀ hallways of the nursing home. Whenever a BD occurs,₅₁₁ the robot will move to that resident. After alleviating₅₁₂ the BD, the robot resumes the predetermined trajec-₅₁₃ tory. The robot moves only to the charger when the₅₁₄ battery becomes critically low. The predefined paths₅₁₅ in the two nursing homes under study are displayed₅₁₆ in Fig. 3.

The main figures of merit for our pro-active position controller and the two baselines are i) the number of BD interventions that the robot can carry out by optimizing its charging cycles, and ii) the Time-To-Interception (TTI). The number of BDs alleviated reflects the global performance of our controller, i.e. it shows the potential number of BDs that could be alleviated by the robot. The TTI reflects the performance of our framework as perceived by an individual resident, i.e. how long does it take before the robot arrives.

5.1. BD dataset collection and analysis

To get better insight in the frequency and type of 530 BD manifestations, the staff of two nursing homes in 531 Ghent, Belgium registered during a period of approx. three 532 months via a smartphone app every time they observed 533 yelling or wandering behavior for any of the participants 534 for which informed consent was obtained. The data col-535 lection procedure, the observational studies and the pro-536 totype deployment of the mobile platform have been ap-537 proved by the ethical committee of UZ Brussels. Patients 538 (or their legal representative) and nursing home staff have 539 given their informed consent prior to the start of the study. 540 In nursing home 1, 15 residents were monitored, of which 541 deceased and 2 dropped out during the registration pe-542 riod. This resulted in 877 registrations of a wandering el-543 derly and 106 registrations of an elderly yelling. In nursing 544

home 2, 10 residents were monitored, and the staff registered 564 times yelling behavior and 279 times wandering behavior

These staff annotations were linked to an estimation of the resident's actual location. To track the out-of-room movement, gateways with Bluetooth Low Energy (BLE) support were installed in several hallways and common living rooms. During the day, most residents are in the common living rooms (CLR), whereas in the evening people tend to spend more time in their room or in the hallway. Residents participating to the study received a Xiami Mi Band wearable or an XY^{\circledR} BLE tag was attached to their wheelchair or walker. With these wearables we were able to track the location of the participants.

Pro-active positioning of the robot is only meaningful if BD events are not randomly spread over time and space. In Fig. 4, we show how the annotated BD observations are distributed over the day. As intuitively expected, a clear drop is seen during the night. We also have less annotations during meal times. One should however be very careful to conclude that there are less BDs during meal times, since this observation may also be caused by the staff being too busy to annotate the BDs. Even if the drop in BDs can be attributed to this effect, one could argue that robot interventions during meal times are anyway not desired since the staff is nearby the residents.

In order to check the underlying spatial patterns of the collected data we have plotted a heatmap of the locations where the annotated BDs took place, for every part of the day, over a time period of 100 days for nursing home 1 and 135 days for nursing home 2. For nursing home 1 we see that there are almost no BDs during the night while in the morning the location of BDs is relatively widely spread. In the afternoon most BDs are located in the common rooms while in the evening most BDs take place in or close by the rooms of the patients. Note however that in nursing home 1 most of the BDs are located in the large room around the bottom right. In nursing home 2 we see that a single room is accounting for most of the BDs.

5.2. Experiment configuration

We evaluate our position control algorithm and the two baseline controllers in a simulator that shifts time while replaying the mobility and BD occurrences per patient. At each time stamp, all cost terms are calculated. To determine the BD anticipation cost C_{BD} (Eq. (5)), we need the BD predictor functions $\mu(.)$. These were constructed by binning daytime in 15 minutes intervals and incrementing the counter of the appropriate bin if a BD was annotated. Generation of this array is additive throughout the simulation: i.e. after simulating one day, the $\mu(.)$ were updated with the corresponding annotations of that day. This allows us to gradually build up knowledge on the patterns, and to account for new residents in the nursing home. In the current experiments, we applied no windowing, i.e. all historical data available until a particular day is taken into account.

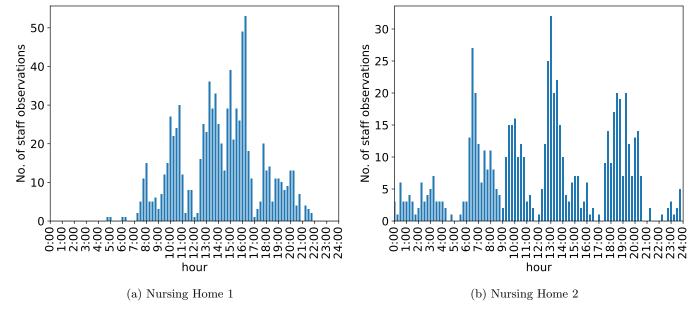


Figure 4: Number of observed BDs for the two different nursing homes for patients who gave ethical consent. Both show the observations in time slots with a length of 15 minutes.

We wish to verify optimal parameters for our frameworks78 in which our robot alleviates as many BDs as possible while579 keeping the TTI as low as possible. The values of the base580 discharge rate c, f_{idle} and f_{charge} (see Eq. (1)) were kept581 constant in all experiments, reflecting a discharge time of 582 3 hours for a full battery in idle time, and a maximum583 charge time of 1 hour. We set the time of one BD allevia-584 tion interaction to 3 minutes, which we deem is a represen-585 tative duration for the type of personalized interventions586 we designed (Ongenae et al., 2017), such as asking a short587 question or playing a song.

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The main experimental parameter is the robot velocity 589 v. Obviously, if the velocity is high the robot can reach 590 a resident exhibiting a BD very fast from any location. 591 Hence, we expect that the differences between our pro- 592 active control framework and both return and patrolling 593 baselines will become smaller with increasing v. However note in practice the maximum speed is limited by safety 594 considerations and/or mechanical constraints.

The position of the charger, $\vec{x}_{charger}$ is our second exper-596 imental parameter. As shown in Fig. 3 and as explained in 597 section 5.1, in both nursing homes we could identify a se-598 lect number of locations where most of the BDs are taking 599 place. Obviously, if the charger is located far from from 600 these regions, the robot must spent more energy on driving 601 to and from the charger. We experimented with two (ex-602 treme) positions of the charger for each nursing home, one603 in a common room where most of the BDs were annotated,604 and one at a far end of the nursing home. These positions,605 labelled 'near' and 'far', are indicated in Fig. 3. Note that606 in practice, safety concerns restrict the possible charger607 locations, e.g. it can not be placed in front of a fire exit.608 Also, the spatial BD distribution might shift over time due609

to changes in the population or the progression of dementia. If the charger is located far away from these regions where most BDs take place the return heuristic is at a bigger disadvantage because the robot will be constantly on the move. When movement is costly this makes the battery drain even faster and much time is wasted on driving to and from the charger. The patrolling baseline is also at a disadvantage whenever the BDs occur far away from the current position on the patrolling path, wasting much time on patrolling in areas which are of less importance. Our cost-based control framework however should position the robot (idle) at optimal positions and only charge when deemed beneficial (i.e. in idle times) or when necessary. On the other hand, if the charger is located near the region where most BDs take place the difference in performance between the frameworks should decrease.

5.3. Number of BDs alleviated

We first wish to verify that our framework alleviates as many BDs as possible. For this we plot α , which equals the total number of alleviated BDs divided by the total number of BDs, versus the velocity v.

As seen in Fig. 5, the number of BDs that the robot can alleviate increases with the velocity since the robot loses less time with navigating to and from the charger position. This observation is further backed up by comparing with the return controller: for low velocities the number of alleviated BDs is low if the charger is positioned far away from where the majority of the BDs take place (right panels in the subfigures). In these situations the robot is spending a lot of time to move to and from the charger position. Our cost-based framework improves the number of alleviated BDs since the robot is only moved towards the charger

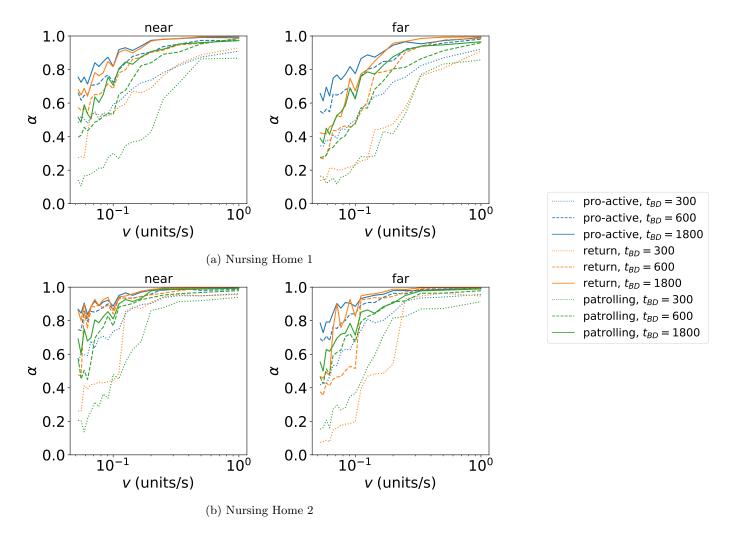


Figure 5: The number of alleviated BDs divided by the total number of BDs as a function of the robot's velocity. The labels 'near' and 'far' on top of each graph indicate the charger position $\vec{x}_{charger}$. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:3:2)$, BD duration = 10 min.

in idle times (or unless it is absolutely necessary). The $_{\rm 630}$ improvement in alleviated BDs for lower velocities is seen in both nursing homes. Note that the results in Figure 5 $_{\rm 631}$ denote a configuration where the battery cost of movement, f_{move} , is larger than the cost of interacting, f_{int} . We believe this is the most common setting. However, for $_{\rm 635}$ completeness, we have included in Appendix A the results $_{\rm 635}$ when f_{int} is larger than f_{moving} .

The dataset only contains the time of annotation, but 637 not the duration of the BD manifestations or the interac-638 tion time necessary to alleviate a BD. We have therefore 639 run simulations with different durations of BDs and evaluated the sensitivity of the number of BDs alleviated. The 641 results can be seen in Figure 5. The results confirm the 642 intuitive expectation that if a BD has a longer duration, 643 the number of BDs alleviated will increase since the robot 644 has a longer time window to intervene.

The BD duration sets an upper limit to the TTI. In the 646 experiments reported in the next subsection we will set 647 the BD duration to 10 minutes since it represents average 648

performance of the robot.

5.4. Time-To-Interception

Next we measure the TTI as a function of the robot velocity, under the same conditions of charger positions and battery cost ratio's as in the previous section. The results are plotted in Fig. 6. (see Appendix A for additional figures for different cost fractions; the conclusions are similar).

In all conditions, the TTI decreases with increasing velocity since the robot can move faster from any location towards the location of a BD manifestation. By comparing the results for charger positions A and B, it can be seen that in both nursing homes the charger position has a very limited effect on the TTI achieved by all controllers. This means that, when considering the TTI, the staff can freely choose where to place the charger station so that it does not block fire exits or frequently visited hallways.

In most experiment conditions, the patrolling baseline has the worst TTI of all three controllers. This was ex-

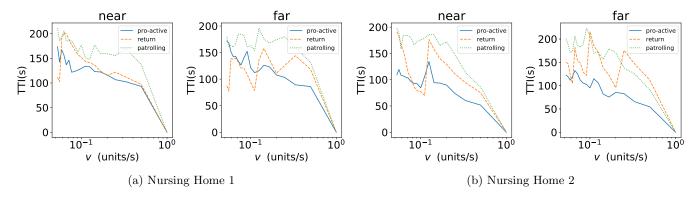


Figure 6: TTI in seconds as a function of robot velocity, for different cost ratio's and different charger positions. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:3:2)$, BD duration of 10 minutes.

pected, since the robot is following a trajectory throughout⁶⁸⁸ the entire nursing home and does not account for the ac-⁶⁸⁹ tual resident location. Our pro-active positioning results⁶⁹⁰ in the lowest TTI in most experiment conditions. Note⁶⁹¹ that the TTI is sometimes reduced by more than a minute⁶⁹² for lower velocities, which is a significant result considering⁶⁹³ that the BDs have a duration of 10 minutes. The influence⁶⁹⁴ of the ratio of battery costs of different actions is minimal.⁶⁹⁵

Only for lower velocities and charger position B, the $_{696}$ return controller achieves lower TTIs. This better perfor- $_{697}$ mance might seem counterintuitive, since charger position $_{698}$ B was chosen as far as possible from locations with fre- $_{699}$ quent BD events. However, these results must be inter- $_{700}$ preted in combination with Figure 5(a), where it can be $_{701}$ seen that the return controller achieves the lowest num- $_{702}$ ber of interventions. The return controller thus intervenes $_{703}$ very fast in a very small number of BD events.

Since our predictor functions $\mu(.)$ accumulate knowledge over time, we have also evaluated if the average TTI de- $_{706}$ creases when more data becomes available. In Figure 7, $_{707}$ we plot the average TTI for each simulated day (see Appendix A for additional figures for different cost fractions). We have calculated the p-value of the coefficient of a linear regression function through the data against the null hypothesis of a zero coefficient (meaning that the number of days has no effect on the obtained TTI). Although we obtain negative slopes for our pro-active position controller all experiment conditions, only for nursing home 2 we obtain p-values < 0.05 to reject the null hypothesis.

6. Conclusion and Future Work

In this paper, we have outlined the different algorithms 720 and control strategies to pro-actively position a mobility- 721 enhanced humanoid robot in order to rapidly approach 3722 person with dementia exhibiting a behavioral disturbance.

The positioning controller presented in this paper can₇₂₄ be refined in several ways. First, we do not account for₇₂₅ periods where the robot is used in leisure activities orga-₇₂₆ nized by the caregivers (bingo, group singing, etc.). If the₇₂₇ planning of these activities is incorporated in the position₇₂₈

control algorithm, we can ensure that the robot is fully charged at the start of the activity.

Second, our algorithm is currently not accounting for the actual position of the caregiver staff. When a caregiver is nearby when a BD is detected, the robot should not be sent and instead move itself to areas where fewer personnel is available. Besides location tracking of the caregiver staff, adding such functionality would require advance activity recognition to determine if a caregiver is actually available to alleviate a BD.

Third, the predictor functions $\mu(.)$ can be refined. Currently the predictor functions are based on accumulating all occurred BDs. If the framework would be used on longer time scales, one need to remove the BDs from deceased residents, or one would have to investigate the progression rate of dementia, and if this translated in changes in BD manifestations. If sensor and wearable data can be analyzed in near real-time, one could even imagine a real-time BD risk assessment algorithm that continuously adjusts the predictor functions.

Fourth, the current framework is purely reactive: a robot interaction is only started in response to a BD event. We could extend the framework to also plan robot interactions outside of BD episodes. By having the robot interact more with residents, the robot could potentially contribute to an improvement of the Quality-of-Life and thus prevent BD occurrences. Such additional interactions would also mitigate the risk of exposing sensitive medical information, since in the current framework the proximity of the robot to users is an implicit signal that one or more persons are more likely to have a BD. However, planning such interventions outside of BD episodes will require sufficiently diverse and more elaborate interaction capabilities of the robot.

Lastly, longer term experiments are needed to evaluate the acceptance and effectiveness of the designed solution. Although the cognitive capabilities of residents in a closed room ward are severely degraded, we conjecture that the robot behavior must be sufficiently diverse to maintain an enjoying experience on the long term and have a significant impact on the Quality of Life.

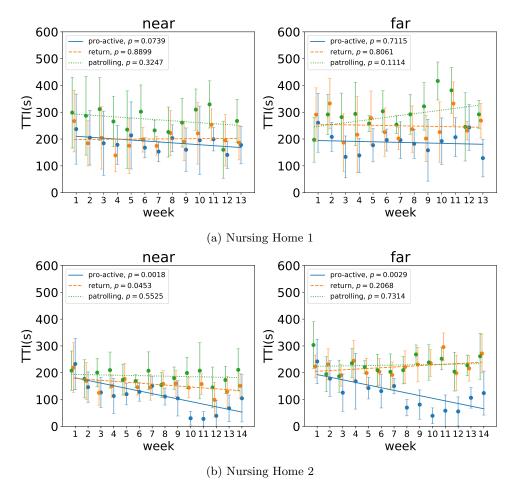


Figure 7: Average TTI of alleviated BDs per week, for charger positions 'near' and 'far'. Errorbars indicate standard deviation of the TTI. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:3:2), v^{-1} = 6$, BD duration = 10 min.

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Acknowledgements

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Appendix A. Additional experimental results for different cost ratios

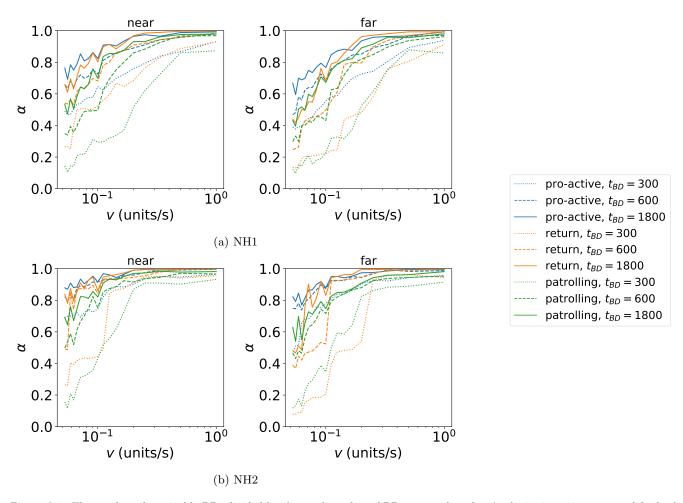


Figure A.8: The number of attainable BDs divided by the total number of BDs versus the robots' velocity in units per second for both NH. The labels 'A' and 'B' on top of each graph refer to the charger position $\vec{x}_{charger}$. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:2:3)$

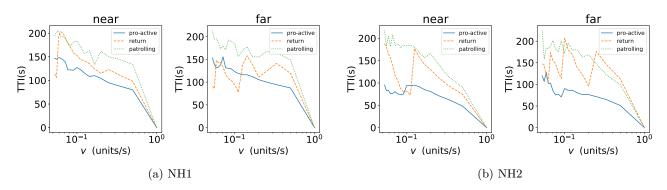


Figure A.9: TTI in seconds as a function of robot velocity, for different cost ratio's and different charger positions. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:2:3)$, BD duration = 10 min.

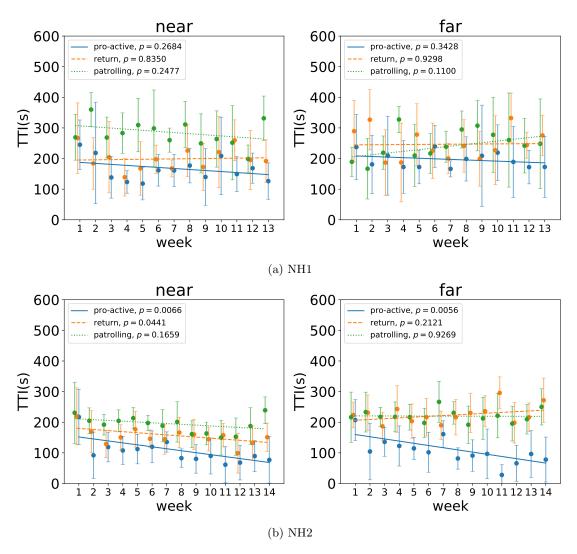


Figure A.10: Linear fit of the TTI in seconds as a function of days simulated, for charger positions 'A' and 'B'. Errorbars indicate standard deviation of the TTIs of all alleviated BDs in one week. Results are plotted for $(f_{idle}: f_{move}: f_{int}) = (1:2:3), v^{-1} = 6$, BD duration = 10 min.