Proceedings of the Thirty-Third International Conference on Automated Planning and Scheduling (ICAPS 2023)

Combining Clinical and Spatial Constraints into Temporal Planning to Personalize Physical Rehabilitation

Alessandro Umbrico[1], Marco Benadduci[2], Roberta Bevilacqua[2], Amedeo Cesta[1], Francesca Fracasso[1], Elvira Maranesi[2], Andrea Orlandini[1], Gabriella Cortellessa[1]

[1] CNR – Institute of Cognitive Sciences and Technologies (CNR-ISTC), Roma, Italy
[2] INRCA IRCCS, Ancona, Italy
alessandro.umbrico@istc.cnr.it, m.benadduci@inrca.it, r.bevilacqua@inrca.it, amedeo.cesta@istc.cnr.it, francesca.fracasso@istc.cnr.it, e.maranesi@inrca.it, andrea.orlandini@istc.cnr.it, gabriella.cortellessa@istc.cnr.it

Abstract

This work investigate temporal planning to synthesize personalized physical rehabilitation programs. The first contribution of the work concerns the representation of (heterogeneous) clinical and spatial constraints into a planning framework. The second contribution is the integration of numerical and symbolic reasoning to synthesize technically valid and coherent plans with respect to different clinical objectives. The experimental section discusses the developed planner from a technical view, assessing solving and personalization capabilities, and from a clinical view, assessing the efficacy of plans on the involved patients.

Introduction

According to the last EU Commission's Report on Aging, the share of the age cohorts above 65 years in the EU population is expected to rise from 20% to 30% by 2070. In contrast, the working-age population is expected to fall from 59% to 51% of the total population [1]. The aging of the population is fostering an increase in the diffusion of neurological disorders that entails a high amount of resources for the healthcare system. The request for continuous monitoring, early diagnosis, and personalized therapy administration would be hard to sustain and very expensive with current (centralized) healthcare models. Investing in sustainable healthcare services becomes therefore urgent given the foreseen increase of assistance demand and shortage of healthcare professionals.

Technological innovation can play a role in overturning such situation by offering new opportunities (Fiorini et al. 2022; Illario et al. 2016). Novel assistive technologies based on Robotics, Internet-of-Things (IoT) and Artificial Intelligence (AI) can positively impact the lives of older adults, and support more efficient care processes (Cesta et al. 2016; Vermesan et al. 2017). The design of innovative services is however challenging and require efforts and contributions from different fields. A *multi-disciplinary methodology* putting domain experts (e.g., therapists, doctors, psychologists), technological experts (e.g., roboticists, AI experts, engineers) and end-users into the decision loop is crucial (Cortellessa et al. 2021).

Among neurological disorders, Parkinson's Disease (PD) is described as the fastest growing in prevalence and strictly linked to the rising of the ageing population (de la Torre et al. 2016; Levy 2007). Within non-pharmacological treatments, studies have demonstrated that regular physical exercise practice has a beneficial effect on balance and gait functional mobility (dos Santos Delabary et al. 2018). Considering recent interventions based on different types of *dance* (Carapellotti, Stevenson, and Doumas 2020), a novel rehabilitation program conducted by a robotic coach and supervised by a physiotherapist have been designed (Bevilacqua et al. 2021). Within this novel rehabilitation program for early stage PD patients, we propose the use of Automated Planning to support therapists in the synthesis of rehabilitation sessions. Rehabilitation sessions are shaped as *dancing lessons* administrating a number of physical stimuli to patients. Such stimuli consist of dancing steps/motions selected by a planner to solicit a certain type of response from patients, according to their rehabilitation needs. We propose a timeline-based planner to combine numerical and symbolic reasoning suitable to decide the (best) set of steps that fit the desired clinical objectives.

Combinatorial capabilities of planning technologies well support therapists to shape rehabilitation programs. Planning implements detailed reasoning on multiple aspects augmenting decisions of therapists. However, the application of AI planning to healthcare and/or rehabilitation domains is not straightforward given the lack of benchmarks, and "standard" models. When planning is applied to contexts where decisions directly affect humans, beyond performance, it is of key importance the *quality* of planned solutions. A correct acquisition and modeling of clinical knowledge is crucial generate plans that are effective. The acquisition and modeling of relevant knowledge requires the non-trivial interaction between planning experts and therapists. The first contribution of this paper thus concerns problem modeling and the acquisition of needed technical and clinical data. The second contribution concerns the integration of numerical and symbolic constraints for the synthesis of plans that are technically valid and coherent with the clinical objectives specified by a therapist. Experiments show the capability of adapting reasoning to specific rehabilitation needs of users.

[1]The 2021 Ageing Report: Economic & Budgetary Projections for the EU Member States (2019-2070).

Physical Therapy and Parkinson's Disease

The rising prevalence of PD is correlated to the ageing of population. Cares aiming at slowing the progression of the disease help PD patients maintaining a good quality of life, feeling active, and reducing costs in the long run (Chaudhuri and Titova 2019). Physical therapy at the early stage of the disease is recommended to counteract the insurgence of motor symptoms (Keus, Hendriks, and Bloem 2004). Recent studies have demonstrated that aerobic physical exercises have beneficial effects on balance and functional mobility (dos Santos Delabary et al. 2018). In this regard, interventions based on different types of *dance* (e.g., Tango or Irish dance) have been designed to recover the normal gait of patients with PD (Carapellotti, Stevenson, and Doumas 2020).

Within the SI-Robotics dance-based rehabilitation program (Bevilacqua et al. 2021), we investigate the use of AI planning to support the synthesis of suitable physical exercises. Many works in the literature investigate the use of AI in healthcare and PD (Belic et al. 2019). AI is used for example to predict the wearing-off of symptoms (Victorino et al. 2021), support decisions (Devarajan, Sreedharan, and Narayanamurthy 2021) or early diagnosis of PD (Parisi, RaviChandran, and Manaog 2018). The majority of these works adopt AI solutions based on deep/machine learning and focus on the diagnosis of the disease. Few works investigate the use of Automated Planning (AP) to support therapists in the synthesis of rehabilitation programs. The work (González, Pulido, and Fernández 2017) for example integrates AP into a control architecture to allow a social robot to physically show motions to a patient during physical rehabilitation. The work (Baschieri, Gaspari, and Zini 2018) uses AP to synthesize stimulation scenarios within a serious game for cognitive rehabilitation. This work pursues an objective similar to us but in a different clinical scenario.

We here propose AP to support the synthesis of physical rehabilitation programs for PD patients. A key aspect of the developed planning framework is the combined reasoning about spatial and clinical effects of stimuli (i.e., motions or dancing steps) that is necessary to synthesize plans that are technically valid and effective from a clinical point of view.

Therapy Design through AI Planning

Compared to a manual definition of the rehabilitation session, the use of a planner aims at improving the quality, the accuracy, and the engagement of the resulting rehabilitation programs. A therapist provides a planner with data about the rehabilitation session (song time, song rhythm, and difficulty level) and the clinical objectives. Given this input, the planner decides a sequence of steps, optimized according to an objective function encoding the specified clinical objective. Planned steps are thus chosen according to the rehabilitation needs of the participating patient (personalization).

A rehabilitation session is structured as a dance lesson where a smart TV plays some music and shows an avatar mirroring the steps (i.e., physical exercises) a patient should perform under the supervision of a therapist. The patient should move within a predefined dancing area, keeping the head pointed to the TV screen. Dancing steps consist of combinations of simple body motions validated by the therapist. The planner controls the avatar of the TV to implement the planned sequence of steps and guide the patient within the session. It is necessary to carefully shape technical and clinical knowledge about steps (*physical stimuli*) and their correlations with the rehabilitation program. This knowledge is indeed essential for the planner to make decisions that are technically valid and coherent with respect to the clinical objective of a session.

Reification of Rehabilitation Knowledge

A planner should know a possibly rich set of stimuli (i.e., dancing steps), and their (cumulative) effects on the environment and health-related aspects of a patient. The acquisition and modeling of such knowledge is not trivial and entails continuous refinements and interactions between planning experts and therapists. We have implemented an iterative modeling processes consisting of three main phases. The therapist is involved in the "modeling loop" and monitors rehabilitation sessions to continuously assess the validity and efficacy of the stimuli generated by the planner. Feedback from the therapist is crucial to refine acquired planning knowledge and improve planning decisions.

Stimuli. The first phase defines the set of physical exercises representing the stimuli of the rehabilitation sessions. Input from therapists is essential to shape the set of basic motions implementing the dancing steps performed by patients during the rehabilitation sessions. These motions constitute the "primitive actions" the planner would consider to achieve the desired rehabilitation objectives. The larger the set of motions the higher the number of alternative sequences (i.e., plans) a planner would take into account when synthesizing a rehabilitation session. The outcome of this first step is a dataset containing a total number of 62 dancing steps. Considering the specific needs of the target users, therapists designed dancing steps as simple motions on lower and upper limbs. Example are "step forward with left foot", "step backward with the right foot and simultaneous rise of the left arm above the shoulder' or "body tilt to the right and simultaneous rise of both arms above the shoulders". Such steps were considered suitable physical exercises that could be administered during a session.

Features. The second phase defines the set of features associated with each physical exercises. Table 1 shows the defined set of features. Features #3 and #4 are technical features characterizing space requirements for the execution of motions. Each motion is assumed to *consume* one "space unit" along a vertical or horizontal axis composing a two dimensional grid. Considering the horizontal axis (feature #3) for example a positive value of space requirement entails a rightward movement of the patient while a negative value a leftward movement. The same apply to the vertical axis (feature #4) where positive values entail forward movements while negative values backward movements. All movements assume a fixed *frontal orientation* of the body of a patient in order to keep constant the reference system. Feature #5 characterizes the rehabilitation level recommended for the session. Not all the defined steps are suitable for all

Feature ID	Name	Type	Description
#1	Description	String	Textual description providing a simple description of the movement a user is supposed to perform.
#2	Step duration	Integer $\in \mathbb{N}^+$	Information about the number of expected beats a user needs to perform the requested movements.
#3	Horizontal space requirement	Integer $\in [-1, 1]$	Information about spatial effects of requested movements with respect to the horizontal/vertical axis of the layout.
#4	Vertical space requirement		
#5	Rehabilitation Level	Integer $\in [1, 4]$	Characterize the training level needed to perform the requested movement.
#6	Energy	Integer $\in [0, 10]$	Estimate the amount of *energetic effort* required for the execution of requested movements.
#7	Coordination	Integer $\in [0, 10]$	Characterize the amount of *coordination effort* required for the execution of requested movements.

Table 1: Technical and clinical features associated to single motions

the patients, depending on their physical conditions and/or the stage of the rehabilitation. This feature allows a therapist to *control* the difficulty level of planned exercises.

Features #6 and #7 are clinical features representing the "effects" that exercises have on the physical coordination and mobility of a patient. The scores associated to each step have been carefully assessed by therapists. *Energy* estimates the metabolic response solicited by the execution of a physical exercise. *Coordination* estimates the effort required for maintaining a good balance of the body while performing a motion. While technical features allow the planner to generate sequences that are technically valid (e.g., keep the patient inside the dancing area), clinical features are necessary to evaluate the fitness of alternative sequences of steps to the clinical objective of the rehabilitation session.

Clinical Objectives. The third phase defines possible clinical objectives of a rehabilitation session. These objectives determine the "reasoning logic" implemented by the planner. The planner optimizes plans (i.e., sequences of steps) with respect to an objective functions by evaluating the features of the selected steps. The particular clinical objective of a session is selected by the therapist who thus determines the way the planner evaluates the cumulative contribution of the clinical features associated with the steps (i.e., the objective function). Two objectives are considered: (i) the *stimulation of physical equilibrium* solicits the body coordination of patients (e.g., administrate stimuli requiring simultaneous and asymmetric movements of lower and upper limbs), and; (ii) the *stimulation of metabolic response* solicits the *energy expenditure* of patients.

Before entering into the details of the implemented reasoning the next section briefly describes the timeline-based planning formalism and the resulting model.

Rehabilitation Sessions as Timelines

The planning system relies on the timeline-based formalism (Cialdea Mayer, Orlandini, and Umbrico 2016) which integrates planning and scheduling through the synthesis of flexible temporal behaviors of domain entities (i.e., timelines) (Jonsson et al. 2000). We here apply timelines to the domain of physical rehabilitation by extending an open-source framework called PLATINUm [2] (Umbrico et al. 2017).

The timeline-based specification of the planning model follows the formalism introduced in (Cialdea Mayer, Orlandini, and Umbrico 2016). Broadly speaking, a model consists of a number of *state variables* describing temporal behaviors of domain features, and a number of *synchronization rules* describing domain constraints among different state variables. State variables specify local constraints characterizing the correct (temporal) dynamics of the modeled domain features. Synchronization rules specify global constraints coordinating state variables to achieve complex goals. The combination of local and global constraints supports the synthesis of valid temporal behaviors (i.e., timelines) achieving the desired goals. A planning problem consists of a set of partially instantiated timelines that specify known *facts* about the initial state of the modeled state variables, and *planning goals* representing states that one or more state variables should achieve within certain temporal intervals. A planning process should synthesize valid and complete temporal behaviors (i.e., timelines) of all state variables such that all domain constraints are satisfied within a known temporal horizon [3].

In the rehabilitation scenario, the timeline-based model specifies rules necessary to synthesize valid sequences of physical exercises. Goals represent requests to plan rehabilitation sessions. In addition to clinical and spatial constraints the model defines rules necessary to comply with the specified rehabilitation level, song rhythm, and song duration.

A *goal state variable* SV_G describes the high-level planning requests specified by a therapist. The set of values V_G contains a default value `Idle` and the values `Equilibrium` and `Stamina` representing requests associated with the clinical objectives, respectively the stimulation of equilibrium maintenance and metabolic response. These two values are enriched with parameters specifying: *song duration*; *song rhythm* and; *rehabilitation level*. A *level state variable* SV_L describes

[2]https://github.com/pstlab/PLATINUm.git

[3]Due to space limitations it was not possible to include a more detailed description of the formalism. We invite readers to refer to the work (Cialdea Mayer, Orlandini, and Umbrico 2016) for a complete and formal description of the planning formalism.

the session steps structuring a rehabilitation session. The set of values V_L contains a default value `Idle` and the values `SessionStepL1`, `SessionStepL2`, `SessionStepL3`, and `SessionStepL4` associated with four rehabilitation levels (see feature #5 in Table 1). Independently from the actual steps selected by the planner, these values determine the number of physical exercises administrated to a patient within a rehabilitation session. The duration bound of these values is set according to the min and max duration of known steps (see feature #2 in Table 1).

A first set of synchronization rules decompose goal values $v_i^G \in V_G$ (e.g., `Stamina` or `Equilibrium`) into values $v_j^L \in V_L$ through `CONTAINS` temporal constrains. The values v_j^L used to decompose a goal value v_i^G depend on the specified rehabilitation level. Token variables associated with the value `SessionStepL1` for example would be considered when the rehabilitation level is set to 1. The number of token variables considered by the synchronization rules depends on the duration and the rhythm of the song selected for the session. The rhythm of a song is expressed in *bpm* (beats per minute) while song and step duration in *beats*. This means that a song with a rhythm of 120 bpm and duration of 90 seconds would contain 180 beats. Considering for example 2 beats as average duration of physical exercises (i.e., dancing steps), a number of 90 session steps would be necessary to complete the session. This kind of reasoning is dynamically performed in order to compute the number of token variables associated with session step values $v_j^L \in V_L$. No ordering constraints between the token variables of the body of these rules are specified within the decomposition. The actual scheduling of session steps is decided by the planner when evaluating spatial constraints.

A *step state variable* SV_S describes all the physical exercises (i.e., dancing steps) known by the planner. The set of values V_S contains a symbol `Step0` denoting a default "rest position" and symbols `Step1`, ..., `Step64` each denoting a physical motion of the dataset defined in conjunction with the therapist. The duration of these values is generally set to 2 beats. Note that the time necessary for the actual execution of a physical motion depends on the selected rhythm of the song. For example a song with a rhythm of 120 bpm entails 2 beats per second and thus a motion of 2 beats should be executed in 1 second. A song with a rhythm of 60 bpm instead entail 1 beat per second and thus a motion of 2 beats should be completed in 2 seconds.

A second set of *synchronization rules* decomposes session steps $v_j^L \in V_L$ into dancing steps $v_k^S \in V_S$ through `CONTAINS` temporal constraints. In principle, each session step $v_j^L \in V_L$ entails a decomposition choice with a branching factor of 62 alternative implementations (the number of defined motions). The selected rehabilitation level of the session reduces this branching factor discarding motions that are associated with a higher level (e.g., a session step `SessionStepL2` would be decomposed into a dancing step with a rehabilitation level equals or lower than 2). These rules encode disjunctive choices necessary to reason about alternative sequences of motions.

Algorithm 1: Timeline-based plan synthesis

Input: $\mathcal{SV}, \mathcal{S}, \mathcal{H}_\pi, \mathcal{H}_\phi$
Output: $\pi = (FTL, R)$
1: $\Pi \leftarrow \emptyset$
2: $\pi \leftarrow$ initialize $(\mathcal{SV}, \mathcal{S})$
3: **while** $\neg$ isSolution $(\pi, \mathcal{SV}, \mathcal{S})$ **do**
4: $\quad \Phi \leftarrow$ flaws $(\pi, \mathcal{SV}, \mathcal{S})$
5: $\quad \Phi^* \leftarrow$ chooseFlaws $(\Phi, \mathcal{H}_\phi)$
6: $\quad$ **for** $\phi \in \Phi^*$ **do**
7: $\quad\quad \Pi \leftarrow$ refine $(\pi, \phi$.resolvers$)$
8: $\quad$ **end for**
9: $\quad \pi \leftarrow$ choosePlan $(\Pi, \mathcal{H}_\pi)$
10: **end while**
11: **return** π

Symbolic and Numerical Reasoning

Based on the symbols and logic rules of the planning model, the planner simultaneously reasons about the structure of a plan and the effects of stimuli on space occupancy and clinical parameters. Algorithm 1 summarizes the general PLATINUm solving procedure. Given a set of input state variables ($\mathcal{SV}$) and synchronization rules ($\mathcal{S}$) a partially instantiated set of timelines π is created according to known facts and goals (row 2). Timelines are refined until a complete and valid behavior is synthesized for each variable $\mathcal{SV}$ (rows 3-8). Each iteration consists of three steps: (i) detect the flaws Φ of the current plan π (row 4); (ii) select some flaw(s) $\Phi^* \subseteq \Phi$ to solve (row 5) and; (iii) compute and apply flaw solutions $\phi \in \Phi^*$ (rows 6-7). Alternative plans are collected into the fringe of the search space Π (row 7). The procedure stops when no flaw is detected on a visited plan π (row 3).

Algorithm 1 is modular and can be extended by integrating new *flaw selection heuristics* $\mathcal{H}_\phi$ and *search strategies* $\mathcal{H}_\pi$. The implemented flaw selection heuristics relies on hierarchical information automatically extracted from the domain specification as presented in (Umbrico, Orlandini, and Cialdea Mayer 2015). The novel contribution of this work specifically concerns the introduction of new *search strategies* $\mathcal{H}_\pi$ to evaluate technical and clinical features of physical stimuli while searching for a valid and effective plan. Developed strategies integrate *pruning mechanisms* to discard plans that violate spatial constraints. They support clinical objectives by integrating different *optimization functions*.

Mapping Timelines to Vector Space of Motions

Planned sequences of steps entail certain combinations of movements that must comply with the spatial constraints of the layout (i.e., the physical "dancing area"). The developed search strategies entail pruning mechanisms to discard plans that violate such spatial constraints. The dancing area is a two dimensional grid $X_{max} \times Y_{max}$, where X_{max} and Y_{max} delimit the maximum reachable coordinates on the horizontal and vertical axes respectively. The starting position of a user is known, $p_0 = (x_0, y_0)$. Each *token* a_i of the *step state*

Algorithm 2: Spatial feasibility check

Input: $\pi = (FTL, R), X_{max}, Y_{max}$
Output: $\top$ if feasible, $\bot$ otherwise
1: $FTL_{\mathcal{S}} \leftarrow$ plannedSteps (π)
2: $\Delta \leftarrow (x_{\Delta} = 0, y_{\Delta} = 0)$
3: $p_0 \leftarrow (x_0, y_0)$
4: **for** $a_i \in \mathcal{A}$ **do**
5: $\quad p_i \leftarrow (x_{i-1} + \text{horizontal}\,(a_i)\,, y_{i-1} + \text{vertical}\,(a_i))$
6: $\quad \Delta \leftarrow (\max\,(x_{\Delta}, |x_0 - x_i|)\,, \max\,(y_{\Delta}, |y_0 - y_i|))$
7: **end for**
8: **if** $x_{\Delta} > (X_{max} - x_0) \vee y_{\Delta} > (Y_{max} - y_0)$ **then**
9: $\quad$ **return** $\bot$
10: **else**
11: $\quad$ **return** $\top$
12: **end if**

variable timeline $FTL_{\mathcal{S}}$ represents a planned exercise [4].

The ordered sequence of tokens $\mathcal{A} = \langle a_1, ..., a_k \rangle$ composing $FTL_{\mathcal{S}}$ can be projected to a vector space in order to evaluate the physical position of a user over time, according to the technical features of Table 1. This allows the planner to compute the maximum deviation $\Delta = (x_{\Delta}, y_{\Delta})$ of the position of the user from p_0 as shown in Algorithm 2.

For each token $a_i \in \mathcal{A}$ of $FTL_{\mathcal{S}}$ the physical position p_i of the user at plan step i is computed to update the *maximum deviation* Δ (rows 4-6). The physical position p_i of a user at *plan step* i is computed by adding the horizontal and vertical translations of planned stimulus to the coordinates x_{i-1} and y_{i-i} of the previous position (i.e., the position at plan step $i-1$, row 5). Coordinates x_i and y_i are then used to compute the absolute distance from the starting position p_0 (row 6). Such distance are then compared to coordinates x_{Δ} and y_{Δ} and used to update the maximum deviation Δ if necessary (row 6). When all tokens $a_i \in \mathcal{A}$ have been considered the obtained maximum deviation Δ is compared to the spatial bounds of the area X_{max} and Y_{max} in order to verify the spatial feasibility of plan π (rows 7-10). If spatial constraints are violated (rows 7-8) then π is pruned.

It is important to point out that the spatial feasibility check of Algorithm 2 analyzes the scheduled tokens of the step state variable $FTL_{\mathcal{S}}$. Namely, it takes into account consolidated sequences of planned steps (row 1) to properly evaluate violations of spatial constraints. The procedure therefore acts as a kind of *pruning mechanism* of partial plans and is integrated into the feasibility check of Algorithm 1 (row 3).

(Clinical) Objective Functions

Clinical objectives entail the maximization of the qualities of a plan with respect to one or more clinical features of Table 1 (i.e., energy and coordination). Two distinct search strategies each addressing a specific clinical objective have been developed and integrated into PLATINUm. In case of *stimulation of physical equilibrium* the strategy would synthesize plans whose stimuli maximize the coordination effort required for the execution of a plan. In case of *stimulation of metabolic response* instead the strategy would synthesize plans whose stimuli maximize the energy effort required for the execution of a plan. Defined strategies follow an A* approach: $f_i\,(\pi) = g_i\,(\pi) + h_i\,(\pi)$.

The cost function $g_i\,(\pi)$ evaluates plans by taking into account tokens $a_i \in \mathcal{A}$ of $FTL_{\mathcal{S}}$. The *heuristic function* $h_i\,(\pi)$ instead evaluates plans by taking into account tokens $w_k^j \in \Omega^j$ associated with the possible refinements $\Omega\,(FTL_{\mathcal{S}}) = \{\Omega^1, ..., \Omega^t\}$ of $FTL_{\mathcal{S}}$. Following well known heuristics like e.g., h_{add} or h_{max} (Bonet and Geffner 1999), $h_i\,(\pi)$ computes the *maximum expected value* of a partial plan π by analyzing sets of tokens $\Omega\,(FTL_{\mathcal{S}})$ that might be part of $FTL_{\mathcal{S}}$ in future refinements.

A search strategy denoted with *objective 1* addresses the clinical objective *stimulation of physical equilibrium*. It maximizes the cumulative coordination effort required by selected stimuli. The evaluation function $f_c\,(\pi)$ is thus defined as follows:

$$\begin{aligned} f_c\,(\pi) = \sum_{a_i \in \mathcal{A}} &\text{coordination}\,(a_i) + \\ &\max_{\Omega^J \in \Omega(FTL_{\mathcal{S}})} \sum_{\omega_k^j \in \Omega^j} \text{coordination}\left(\omega_k^j\right) \end{aligned} \tag{1}$$

where coordination (a_i) and coordination $\left(\omega_k^j\right)$ retrieve the value of the feature *coordination* in Table 1.

A search strategy denoted with *objective 2* addresses the clinical objective *stimulation of metabolic response*. It maximizes the cumulative energy effort required by selected stimuli. The evaluation function $f_e\,(\pi)$ is:

$$\begin{aligned} f_e\,(\pi) = \sum_{a_i \in \mathcal{A}} &\text{energy}\,(a_i) + \\ &\max_{\Omega^J \in \Omega(FTL_{\mathcal{S}})} \sum_{\omega_k^j \in \Omega^j} \text{energy}\left(\omega_k^j\right) \end{aligned} \tag{2}$$

where energy (a_i), energy $\left(\omega_k^j\right)$ retrieve the value of the feature *energy* in Table 1.

Experimental Assessment

This section shows an experimental evaluation of the planning framework.It first shows the technical feasibility of the planner. Regardless of the solving time, the results show the desired capabilities of adapting the "qualities" of generated plans to different clinical objectives. This was a primary requirement with respect to the use of the planner in the rehabilitation program. This section then discusses some results on real patients collected during the actual experimentation. The discussion specifically focuses on two patients with distinct clinical objectives showing the effectiveness of the designed rehabilitation program.

[4] A token a_i instantiates a state variable value v_i over a flexible temporal interval $[e_i, e_i^{'}]$, $[d_i, d_i^{'}]$ composing the timeline of the related state variable, see (Cialdea Mayer, Orlandini, and Umbrico 2016) for further details.

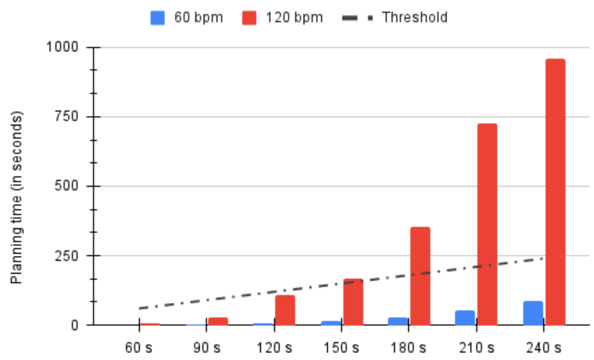


Figure 1: Average planning time.

Technical Evaluation

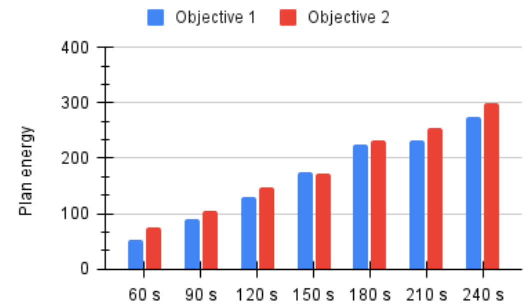
The reasoning capabilities are assessed on a number of planning problems of growing size. All problems consider a physical layout with $X_{max} = 8$ and $Y_{max} = 8$ denoting the bounds of the “dancing area”. A number of problem instances are thus defined by varying the following parameters: (i) *song time* with values 60, 90, 120, 150, 180, 210 and 240 seconds; (ii) *song bpm* with values 60 bpm and 120 bpm; (iii) *rehabilitation level* with values from 1 to 4. Two planning configurations are defined: (i) *objective 1* uses the search strategy addressing *stimulation of equilibrium* through Equation 1, and; (ii) *objective 2* uses the search strategy addressing *stimulation of metabolic response* through Equation 2. Planners are run on all problem instances for a total number of 112 experiments (56 for each configuration) [5].

Figure 1 shows the performance of the two configurations. Both solve all problems instances. The bar chart aggregates the results comparing performances on problems with different song bpm. The threshold denotes the song duration and gives a reference for the evaluation of planning time.

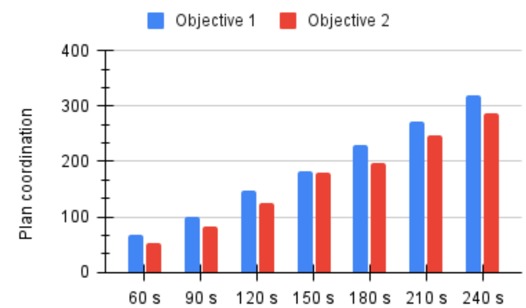
Problems with *60 song bpm* are solved quite efficiently. In all cases the planning time is significantly under the threshold (85 seconds for song duration of 240 seconds). Performance instead get worse for songs with 120 bpm. The planning time is significantly higher than the threshold for song duration of 210 and 240 seconds. Although planning configurations struggle in solving problems with songs of 120 bpm, observed performances are suitable for the deployment on the rehabilitation scenario. Songs used for the actual rehabilitation indeed mainly rely on a rhythm of 60 bpm. Few songs use a rhythm of 120 bpm (maximum duration within 200 seconds).

Most importantly, Figure 2 shows the qualities of synthesized plans. Figure 2(a) compares the cumulative *energy effort* while Figure 2(b) compares the cumulative *coordination effort*. Notably, the two configurations synthesize plans “pushing” different qualities according to the specified clinical objective. Figure 2(a) shows indeed that configuration

[5] Runs made on a workstation with 2,8 GHz quad-core CPU and 16 GB RAM.

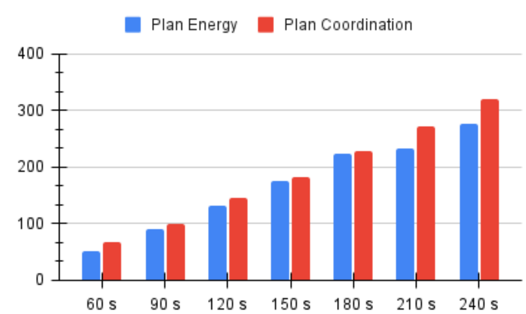


(a)

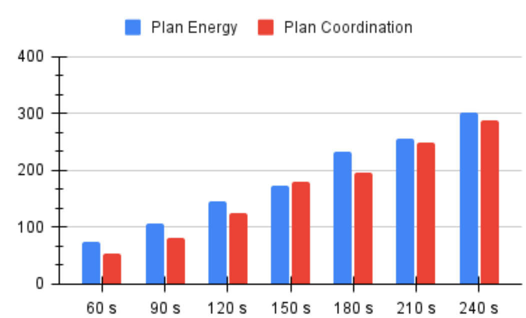


(b)

Figure 2: Comparison of plans stimulating equilibrium (*objective 1*) and metabolic response (*objective 2*): (a) plan energy and; (b) plan coordination.



(a)



(b)

Figure 3: Comparison of average energy and coordination of plans stimulating: (a) equilibrium (*objective 1*) and; (b) metabolic response (*objective 2*).

objective 2 always synthesize plans with *energy effort* higher than plans synthesized by configuration *objective 1*. Conversely, Figure 2(b) shows that configuration *objective 1* always synthesize plans with *coordination effort* higher than plans synthesized by configuration *objective 2*. A comparison of the qualities of the plans synthesized by the same configuration confirms this result. According to Figure 3(a) and Figure 3(b), plans generated by configuration *objective 1* always have coordination effort higher than the energy effort, while plans generated by configuration *objective 2* always have energy effort higher than coordination effort.

Feasibility Assessment in the Field

Given the discussed technical results, the planner was deployed on a novel monitoring service specifically designed and integrated in the daily activity of the Rehabilitation and Physiotherapy Operating Unit of INRCA IRCCS [6] in Ancona (Italy) that routinely conducts group therapy with older PD patients at different stage of disease severity.

A clinical study was designed with the aim of verifying the acceptability of the novel therapy by patients diagnosed with early stage PD. More details on the study protocol can be retrieved in (Bevilacqua et al. 2021). The (ethically validated) experimental protocol consisted of 16 rehabilitation sessions, one hour duration each and distributed over 8 weeks. Within each sessions, traditional physical exercises (e.g., mobility, strengthening, stretching, coordination and breathing exercises) were offered followed by 20 minutes of dance-based stimuli (i.e., steps planned by the integrated planner). The evaluation of the outcome of the study concerned patient's quality of life, daily autonomy, motor performance, and acceptability of the system by the patient.

In this feasibility evaluation phase, nine subjects among those joining the telerehabilitation group of the rehabilitation unit of INRCA IRCCS, met the inclusion criteria. Figure 4 shows a patient joining a session with the planner synthesizing the dancing steps that are administered through the TV. While more details regarding the clinical-related findings can be found elsewhere (Bevilacqua et al. 2022), preliminary results about the acceptability suggest that the novel service was perceived as usable and effective in treating conditions typical of PD. One of the aim of the study was to analyze the modification of dimensions related to the general functional status of patients in terms of gait, fear of falling, cardio-respiratory performance, motor symptoms related to PD, and quality of life. In this regard, we here focus on the results of two patients of the study to discuss the contribution of the planner, by illustrating improvements in specific metrics measured at the baseline (T0), at midterm after 4 weeks (T1), and at the end of the rehabilitation session after 8 weeks (T1).

- Patient G.C., is male, born 09/10/1953, with stage 2 according to Hoen and Year scale (Hoehn and Yahr 1967), the disease was diagnosed 10 years earlier. Objective examination demonstrates poverty of general movements, bradykinesia, gait pattern with small and crawling steps, minimal rigidity. Tremors and freezing were not appreciated during evaluation and treatment. The primary aim for the patient was to improve gait pattern, reduce the risk of falling, and increase speed. The patient showed consistent improvement in the *six minute walk test* (6MWT) (Enright 2003) and Timed Up and Go (TUG) (Balke 1963). In the 6MWT trial, the patient went from 310mt (T0), 360mt (T1) and 428mt (T2). In the TUG trial, the patient significantly reduced the time from 14.97 seconds to 10.2 seconds. Also at the E.O. by the therapist, an improvement in gait pattern could be appreciated.
- Patient R.C, is female, born 2/23/1942, with a stage 2 according to Hoen and Year scale, diagnosis occurred 6 years earlier. The objective examination shows only an unsteady gait and reduced balance in static and dynamic phases although no history of falls in the last year. The objective examination and assessments showed reduced balance in both dynamic and static phase, assessed through the *short physical performance battery* (SPPB) (Pavasini et al. 2016) and TUG. The primary goal was to provide greater safety and reduce the risk, albeit minimal, of falling. At the end of the treatment, a significant improvement in TUG was appreciated, which was consistently reduced from 14.66 seconds to 9.56 seconds. The SPPB scale improved in all its items showing an improvement in the total score from 8 to 10.

According to these results we can confirm the efficacy of the planner in generating plans suitable for the different objectives of the rehabilitation sessions.

Concerning acceptability, Figure 5 shows the aggregated results measured through the UTAUT scale (Venkatesh et al. 2003). The feedback of the patients was overall positive judging the technology as acceptable. The system was perceived as useful (PU), easy to use (PEOU), and enjoyable (PENJ). Furthermore, patients felt a low level of anxiety (ANX) during the exercises and trusted the System (TR). Nevertheless, the low score on facilitating conditions (FC) reports doubts about the capability of supporting the use of the technology with the existing organizational and technical infrastructure.

Conclusions and Future Works

The paper shows the use of timeline-based planning for the synthesis of *physical stimuli* tailored to the *rehabilitation needs* of patients. An experimental evaluation shows the efficacy of the developed framework in adapting the *qualities* of plans to the *clinical objectives* specified by a therapist. Next steps will concern the continuous use of the tool during the designed experimentation in real settings. Furthermore we will investigate the enhancement of solving capabilities by integrating *learning* at both symbolic and numerical level. For example we plan to investigate the extraction of *landmarks* or quality bounds that (according to the objective) can be used to synthesize *specialized heuristics* and improve *pruning mechanisms*.

[6] https://www.inrca.it/inrca/?lingua=en

Figure 4: Deployment of the planner into the rehabilitation scenario. The planner is integrated with a game engine showing the steps the patient should perform on a TV screen. The game engine is in charge of "executing" plans by playing the selected song, and prompting the planned steps according to the selected rhythm (60 or 120 bpm).

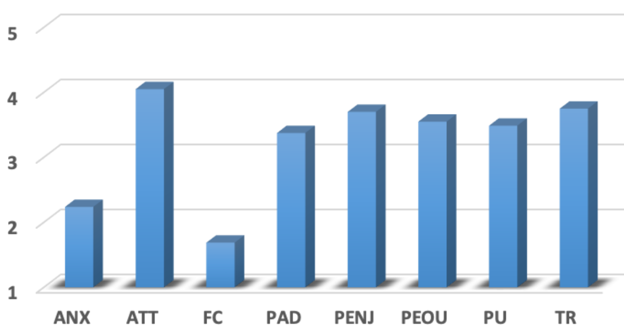


Figure 5: Results of the UTAUT scale. Scale from 1 to 5 where 1=strongly disagree and 5=strongly agree. ANX = Anxiety; ATT= Attitude towards Technology; FC= Facilitating Conditions; PAD= Perceived Adaptability; PENJ= Perceived Enjoyment; PEOU= Perceived Ease of Use; PU=Perceived Usefulness; TR= Trust.

Acknowledgements

This work is supported by "SI-ROBOTICS: SocIal ROBOTICS for active and healthy ageing" project (Italian M.I.U.R., PON – Ricerca e Innovazione 2014-2020 – G.A. ARS01_01120). CNR authors are partially supported by Italian MUR and the PNRR research project "Fit4MedRob- Fit for Medical Robotics" - Piano Nazionale Complementare D.D. n. 931 6/6/2022 Cod. PNC0000007. CNR authors are also members of the EU project TAILOR "Foundations of Trustworthy AI Integrating Learning, Optimisation and Reasoning" GA#952215.

References

Balke, B. 1963. *A simple field test for the assessment of physical fitness*, volume 63. Civil Aeromedical Research Institute.

Baschieri, D.; Gaspari, M.; and Zini, F. 2018. A Planning-Based Serious Game for Cognitive Rehabilitation in Multiple Sclerosis. 214–219. New York, NY, USA: Association for Computing Machinery.

Belic, M.; Bobic, V.; Badza, M.; Solaja, N.; Duric-Jovicic, M.; and Kostic, V. S. 2019. Artificial intelligence for assisting diagnostics and assessment of Parkinson's disease—A review. *Clinical Neurology and Neurosurgery*, 184: 105442.

Bevilacqua, R.; Benadduci, M.; Bonfigli, A. R.; Riccardi, G. R.; Melone, G.; La Forgia, A.; Macchiarulo, N.; Rossetti, L.; Marzorati, M.; Rizzo, G.; Di Bitonto, P.; Potenza, A.; Fiorini, L.; Cortellessa Loizzo, F. G.; La Viola, C.; Cavallo, F.; Leone, A.; Rescio, G.; Caroppo, A.; Manni, A.; Cesta, A.; Cortellessa, G.; Fracasso, F.; Orlandini, A.; Umbrico, A.; Rossi, L.; and Maranesi, E. 2021. Dancing With Parkinson's Disease: The SI-ROBOTICS Study Protocol. *Frontiers in Public Health*, 9.

Bevilacqua, R.; Benaduci, M.; Riccardi, G. R.; Melone, G.; La Forgia, A.; Macchiarulo, N.; Rossetti, L.; Marzorati, M.; Rizzo, G.; Di Bitonto, P.; Potenza, A.; Fiorini, L.; Cornacchia Loizzo, F. G.; La Viola, C.; Cavallo, F.; Leone, A.; Rescio, G.; Caroppo, A.; Manni, A.; Cesta, A.; Cortellessa, G.; Fracasso, F.; Orlandini, A.; Umbrico, A.; Amabili, G.; Rossi, L.; and Maranesi, E. 2022. SI-ROBOTICS System: a preliminary study on usability of a rehabilitation program in patients with Parkinson's disease. In *2nd Workshop on sociAL roboTs for peRsonalized, continUous and adaptIve aSsisTance (ALTRUIST)*, number 3323 in AIxIA Series of CEUR-WS Workshop Proceedings, 22–32. Aachen.

Bonet, B.; and Geffner, H. 1999. Planning as Heuristic Search: New Results. In *Proceedings of the 5th European Conference on Planning: Recent Advances in AI Planning*, 360–372. Berlin, Heidelberg: Springer-Verlag.

Carapellotti, A. M.; Stevenson, R.; and Doumas, M. 2020. The efficacy of dance for improving motor impairments, non-motor symptoms, and quality of life in Parkinson's disease: A systematic review and meta-analysis. *PLOS ONE*, 15(8): 1–28.

Cesta, A.; Cortellessa, G.; Orlandini, A.; and Tiberio, L. 2016. Long-Term Evaluation of a Telepresence Robot for the Elderly: Methodology and Ecological Case Study. *I. J. Social Robotics*, 8(3): 421–441.

Chaudhuri, K. R.; and Titova, N. 2019. Societal Burden and Persisting Unmet Needs of Parkinson's Disease. *European Neurological Review*, 14(1): 28–35.

Cialdea Mayer, M.; Orlandini, A.; and Umbrico, A. 2016. Planning and execution with flexible timelines: a formal account. *Acta Informatica*, 53(6-8): 649–680.

Cortellessa, G.; Benedictis, R. D.; Fracasso, F.; Orlandini, A.; Umbrico, A.; and Cesta, A. 2021. AI and robotics to help older adults: Revisiting projects in search of lessons learned. *Paladyn, Journal of Behavioral Robotics*, 12(1): 356–378.

de la Torre, R.; de Sola, S.; Hernandez, G.; Farré, M.; Pujol, J.; Rodriguez, J.; Espadaler, J. M.; Langohr, K.; Cuenca-Royo, A.; Principe, A.; Xicota, L.; Janel, N.; Catuara-Solarz, S.; Sanchez-Benavides, G.; Bléhaut, H.; Dueñas-Espín, I.; del Hoyo, L.; Benejam, B.; Blanco-Hinojo, L.; Videla, S.; Fitó, M.; Delabar, J. M.; and Dierssen, M. 2016. Safety and efficacy of cognitive training plus epigallocatechin-3-gallate in young adults with Down's syndrome (TESDAD): a double-blind, randomised, placebo-controlled, phase 2 trial. *The Lancet Neurology*, 15(8): 801 – 810.

Devarajan, J. P.; Sreedharan, V. R.; and Narayanamurthy, G. 2021. Decision Making in Health Care Diagnosis: Evidence From Parkinson's Disease Via Hybrid Machine Learning. *IEEE Transactions on Engineering Management*, 1–13.

dos Santos Delabary, M.; Komeroski, I. G.; Monteiro, E. P.; Costa, R. R.; and Haas, A. N. 2018. Effects of dance practice on functional mobility, motor symptoms and quality of life in people with Parkinson's disease: a systematic review with meta-analysis. *Aging Clinical and Experimental Research*, 30(7): 727–735.

Enright, P. L. 2003. The Six-Minute Walk Test. *Respiratory Care*, 48(8): 783–785.

Fiorini, L.; Sorrentino, A.; Pistolesi, M.; Becchimanzi, C.; Tosi, F.; and Cavallo, F. 2022. Living With a Telepresence Robot: Results From a Field-Trial. *IEEE Robotics and Automation Letters*, 7(2): 5405–5412.

González, J. C.; Pulido, J. C.; and Fernández, F. 2017. A three-layer planning architecture for the autonomous control of rehabilitation therapies based on social robots. *Cognitive Systems Research*, 43: 232–249.

Hoehn, M. M.; and Yahr, M. D. 1967. Parkinsonism. *Neurology*, 17(5): 427–427.

Illario, M.; Vollenbroek-Hutten, M. M. R.; Molloy, D. W.; Menditto, E.; Iaccarino, G.; and Eklund, P. 2016. Active and Healthy Ageing and Independent Living 2016. *Journal of Aging Research*, 2016: 1–3.

Jonsson, A.; Morris, P.; Muscettola, N.; Rajan, K.; and Smith, B. 2000. Planning in Interplanetary Space: Theory and Practice. In *AIPS-00. Proceedings of the Fifth Int. Conf. on AI Planning and Scheduling*.

Keus, S.; Hendriks, E.; and Bloem, B. 2004. KNGF guidelines for physical therapy in patients with Parkinson's disease. *Dutch J Physiother*, 114(3).

Levy, G. 2007. The Relationship of Parkinson Disease With Aging. *Archives of Neurology*, 64(9): 1242–1246.

Parisi, L.; RaviChandran, N.; and Manaog, M. L. 2018. Feature-driven machine learning to improve early diagnosis of Parkinson's disease. *Expert Systems with Applications*, 110: 182–190.

Pavasini, R.; Guralnik, J.; Brown, J. C.; di Bari, M.; Cesari, M.; Landi, F.; Vaes, B.; Legrand, D.; Verghese, J.; Wang, C.; Stenholm, S.; Ferrucci, L.; Lai, J. C.; Bartes, A. A.; Espaulella, J.; Ferrer, M.; Lim, J.-Y.; Ensrud, K. E.; Cawthon, P.; Turusheva, A.; Frolova, E.; Rolland, Y.; Lauwers, V.; Corsonello, A.; Kirk, G. D.; Ferrari, R.; Volpato, S.; and Campo, G. 2016. Short Physical Performance Battery and all-cause mortality: systematic review and meta-analysis. *BMC Medicine*, 14(1): 215.

Umbrico, A.; Cesta, A.; Cialdea Mayer, M.; and Orlandini, A. 2017. PLATINUm: A New Framework for Planning and Acting. *Lecture Notes in Computer Science*, 498–512.

Umbrico, A.; Orlandini, A.; and Cialdea Mayer, M. 2015. Enriching a Temporal Planner with Resources and a Hierarchy-Based Heuristic. In *AI*IA 2015, Advances in Artificial Intelligence*, 410–423. Springer.

Venkatesh, V.; Morris, M. G.; Davis, G. B.; and Davis, F. D. 2003. User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3): 425–478.

Vermesan, O.; Bröring, A.; Tragos, E.; Serrano, M.; Bacciu, D.; Chessa, S.; Gallicchio, C.; Micheli, A.; Dragone, M.; Saffiotti, A.; Simoens, P.; Cavallo, F.; and Bahr, R. 2017. Internet of robotic things : converging sensing/actuating, hypoconnectivity, artificial intelligence and IoT Platforms. In *Cognitive hyperconnected digital transformation : internet of things intelligence evolution*, 1–35.

Victorino, J. N.; Shibata, Y.; Inoue, S.; and Shibata, T. 2021. Predicting Wearing-Off of Parkinson's Disease Patients Using a Wrist-Worn Fitness Tracker and a Smartphone: A Case Study. *Applied Sciences*, 11(16).