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ABSTRACT

Conventional gait rehabilitation methods have the risk of alienating the patient due to their monotonous nature, thus negatively impacting the effectiveness of gait training. Modern technologies can help provide patients with better support, safety and immersive experience during training. However, physiotherapists cannot be required to master those technologies, nor to spend much time designing a more varied and engaging treatment for each patient. In this paper, we argue that adaptive gamified gait rehabilitation based on procedural content generation (PCG) can effectively support physiotherapists in achieving such customized outcomes. We propose a generic adaptation scheme to steer the generation of movement challenge levels based on player modeling and therapists' intervention. Our approach features two difficulty adjustment strategies: parameter progression schemes and integration of multiple therapy goals. These strategies are applicable to the personalization of a wide range of gait rehabilitation goals. We implemented this approach in a standalone prototype for supporting gait training with the RYSEN system, a three-dimensional overground body weight support system. From our assessment with physiotherapists, we conclude that our PCG-based adaptive method effectively assists therapists in (i) offering a broad diversity in gait exercises to a wide group of patients, and (ii) dynamically tailoring challenge levels for a variety of gait tasks.

KEYWORDS

Gait rehabilitation, Procedural content generation, Player model, Game adaptivity, Games for health

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1 INTRODUCTION

Gait impairments are serious motor symptoms caused by prevalent neurological disorders such as stroke and Parkinson's disease. To help patients recover from long-term gait deficits, physiotherapists usually prescribe a set of gait exercises, and possibly adapt them as needed during the gait rehabilitation process. Nevertheless, it is not a trivial task for physiotherapists to optimize the recovery process and outcomes in conventional gait rehabilitation. First and foremost, patients are required to perform repetitive movements in order to regain motor functions [3]. Unfortunately, repeating monotonous tasks on a daily basis reduces patients' motivation to adhere to the therapy schedule, especially when they have to overcome discomfort and physical limitations. Moreover, traditional methods tend to require considerable effort from the physiotherapist's side. On the one hand, the physiotherapist should always be by the patient's side to provide the necessary support and ensure safety. On the other hand, the physiotherapist is responsible for monitoring the performance of each patient, providing timely advice on movements, as well as making necessary adjustments to today's training plan.

Serious games, seeking to balance *learn* and *play* components, are emerging as a promising tool in the gait rehabilitation domain [13]. The make-believe gameplay can offer patients the chance to experience real-life challenges while reducing possible negative feelings [19]. Their integration with modern technologies is opening up numerous applications and research innovations. An example is a robotic system that provides sufficient support and protection for patients during gamified training. Besides, patient-related data collected during training can be provided to physiotherapists, helping them to better understand and track patients' performance based on such quantitative feedback. This paper proposes to leverage serious games as an effective physiotherapeutic vehicle, by focusing on the deployment of player-centered adaptive gameplay while always keeping the physiotherapists in the loop.

In this context, adaptivity refers to the ability to adapt the challenge level to fit the patients' skills and performance at each moment. In rehabilitation, this personalization can be seen as having a double purpose: keeping a patient motivated along a routine procedure, and reducing anxiety and discomfort due to a physical ailment or treatment. As to the former, there is solid experience on methods to keep players in the flow [5]; regarding the latter, there is also increasing interest on the effective deployment of games in a variety of forms and health domains [2].

To achieve this, a player model is usually maintained, and used to steer subsequent content adaptation [9]. It takes the player-centred data as input, derives their relevant current skills, and predicts the right challenge for the upcoming level [17]. Several player modeling techniques in recent adaptive games are rather *ad-hoc*, as they are made for a specific context and thus hinder their re-usability. Apart from player modeling, adaptation mechanism is the other main aspect of an adaptive game [18]. Based on the analysis of the player model, the in-game interventions then adjust the difficulty level correspondingly. Currently, one limitation is that the importance of diversity in difficulty transition is often disregarded, making these

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transitions rather monotonous. Mostly, only one difficulty-related parameter is adjusted in each game during the whole training process. Procedural content generation (PCG) is a powerful technique for adaptation mechanisms [16]. By generating the game world automatically based on algorithms, each level is able to provide less predictable and more appealing content [8, 23]. However, no automated game system should take over physiotherapists' place in gait rehabilitation. To help physiotherapists better master the challenges offered, timely control options have to be provided.

We propose a generic method to adaptively steer a game level generator for gait rehabilitation in a clinical environment. A player model is created which takes performance-related data as input and assesses patient progress. The customized parameter values can then be applied to steer the level generator. For each gait exercise, multiple parameters can determine its difficulty evolution. Two progression schemes are proposed to assist physiotherapists in determining appropriate challenge levels to patients at different conditions. In addition to adding variation to the gameplay, the procedural content generator makes it possible to integrate two (or more) exercises into one game scene in real-time. Physiotherapists can then capitalize on this to create a new layer of challenge.

This research approaches the question *'how can adaptive steering of a procedural game level generator support a physiotherapist in achieving the desired gait rehabilitation goals?'* To answer it, we implemented our adaptation mechanism in a standalone prototype for gait recovery that uses a three-dimensional overground body weight support system RYSEN [22]. A mapping between therapy goals and gameplay movement to achieve those goals was elaborated. Together with therapists, we developed four games aimed at improving gait adaptability and overcoming motor-cognitive dual-task interference. Our prototype includes a simple interface that allows physiotherapists to easily setup and control rehabilitation sessions, as well as approve the challenge progression scheme proposed by the adaptive system.

2 RELATED WORK

To continuously improve the motor function of patients over a long recovery period, a serious game should preferably take on a player-centred strategy that adapts to the player's needs and skills before and/or during the game [15]. Difficulty level is an essential factor to be adapted in the design of game for rehabilitants, as a proper level of challenge can enhance patients' motivation and maximize their effort to overcome physical barriers.

Adaptation that happens prior to the start of each game session is called off-line adaptation. In a game designed for gait training [10], the therapists, based on the recorded performance of each patient, adjusted the values of difficulty-related parameter at the beginning of each game, which included the irregularity of the stepping targets, the acceleration of a target area, etc. One drawback of merely relying on such methods is that they tends to expose physiotherapists to numerous parameters, which values are not identical for each patient. Moreover, most of them are supposed to be updated with the improvement of patients' performance and day-to-day health conditions. Such complexity can cost therapists much time and energy, thus limiting the number of patients they can supervise daily.

On-line adaptation makes an automatic adjustment based on gameplay-specific data in real-time. Dynamic difficulty adjustment (DDA), is the most utilized method to create adequate challenge levels for players [15] and keep them in *flow* [6]. Player modeling is usually applied in DDA to predict the difficulty level. Pirovano et al. [21] applied a Quest Bayesian adaptive method [25] to fit each patient's performance in posture and balance rehabilitation. For each mini-game, the therapist identified one game parameter that affects the task difficulty. The Quest Bayesian method is then applied to adapt this parameter after each trial based on the performance of the patient and the pre-set success rate. The determination of parameters in this probabilistic player model, however, was based on healthy people. To achieve better estimation, most likely a larger and varied population should be required.

Diversity in difficulty adjustment has been rarely paid attention to. In a game designed for upper-limb rehabilitation [20], only three states were provided, corresponding to easy, medium, and hard difficulty level. A limitation of this work is that three difficulty intervals are not enough to provide a smooth difficulty transition. Besides, only one parameter was changed during the adaptation, despite the fact that, in their game design, various parameters affected the difficulty.

In a personalized training module Spheroids [4], four parameters are characterized to describe the difficulty of the training task. One focus of their work is to determine the contribution of each parameter to the overall difficulty, where they applied a quadratic model and fitted it with experimental data. Once the difficulty weight of each parameter was decided, the different combinations of parameters could offer different game experiences at the same difficulty level. However, such a way of defining the difficulty greatly increases the development cycle. Considering the small group of target players and short lifecycle of a rehabilitation game [11], its efficiency turns out rather low.

For rehabilitation purposes, PCG is being adopted to generates diverse game content, including virtual environment, game objects, game levels, etc. Compared to hand-crafted levels, its flexibility and diversity make it potentially suitable for rehabilitation context. Dimovska et al. [8] first applied PCG in rehabilitation with the game ReSkii, for balance and persistence improvement. Prior to the start of gameplay, the snow mountain terrain is generated with a zigzag pattern based on Catmull-Rom Splines. Gates are procedurally placed on the right and left sides for the 'skiing' patient to reach.

PCG was also used in rehabilitation to create virtual environments. For example, Kern et al. [14] applied PCG to assist in creating an inhabited green forest which aimed at encouraging patients to walk using a reward system. The application procedurally placed the vegetation models and reward elements.

To sum up, most adaptation approaches take a player's performance as the input, for which the player modeling is critical. However, most models so far are game-specific and/or require large empirical data, which prevents them from being applied in other domains and games. When adjusting difficulty levels, a lot of methods focused only on the progression of one single parameter. Although some approaches sought to manipulate multiple parameters diversely, they mostly lack in efficiency and reusability. Using PCG techniques for rehabilitation has also the advantage of largely increasing the variety of game content. We can therefore conclude

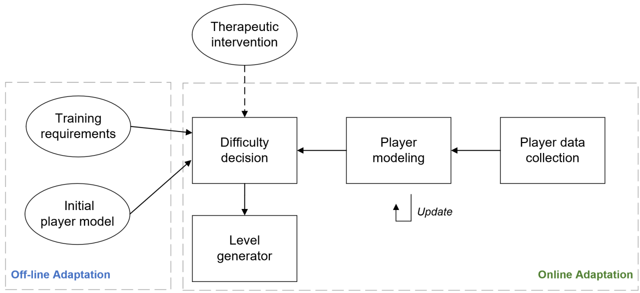


Figure 1: Adaptation loop for each task training in gait rehabilitation

that, when properly integrated with suitable adaptation schemes, its use in gait rehabilitation is very promising.

3 ADAPTATION SCHEME

We propose a generic adaptation scheme that aims at providing a fine-tuned level of challenge for gait rehabilitation in a clinical environment; see Figure 1.

The off-line adaptation is based on the training requirements and the initial player model. The training requirements comprise which tasks the therapist wants the patient to accomplish, as well as an estimation of their duration. Based on the therapist's decision for the starting difficulty level, the procedural generator can provide initial personalized game content for the patient. The online adaptation, on the other hand, is responsible for dynamically adjusting the challenges for the patient in real-time. It comprises player skills prediction as well as difficulty decision. To better assist physiotherapists, they are presented with the recommended difficulty levels, for possible adjustment and/or confirmation. Based on the values of each difficulty-related parameter, the procedural level generator automatically generates the suitable game content to stimulate the desired task-specific gait movements.

3.1 Player modeling

An essential question in any adaptation scheme concerns *when* to adjust the difficulty level [15]. The assessment of players' performance and prediction of their current skills are critical to answer it.

We propose a player model based on two aspects of player performance: **accuracy** and **efficiency**. Accuracy relates to the amount of 'mistakes' a player commits during one level segment, while efficiency relates to the amount of time taken by a player to accomplish a task. On the one hand, ensuring accurate movement can always guide patients to stretch their bodies within an acceptable range and help them avoid getting injured. On the other hand, increasing the movement speed is viewed as a cost-free strategy [7], which is able to increase the training intensity and thus speed up the motor learning process.

For each therapeutic task, there can be several factors describing the performance, which relate to either the accuracy and efficiency aspects above. Supposing a training task requires a patient to perform a certain gait movement on a surface, there could be at least two factors describing the performance in each level segment:

- U: the count of undesirable movements, e.g. the patient fails to stretch his/her body to a proper extent
- V: average moving speed, denoting the mean velocity over the current level

Equation 1 quantitatively describes the impact of each factor on a player's current performance. The rationale of this player model is to compare the player's status data with a collection of reference values, which can be set by physiotherapists based on experience or assessment sessions. The collected player-related data is represented with the subscript ***measure*** and the reference values at current level are highlighted with the subscript ***currentRef***. W_A and W_E represent the weights for accuracy and efficiency respectively.

$$currentScore = 2 \cdot (W_A \cdot (\boldsymbol{H}(U_{\text{currentRef}} - U_{\text{measure}}) - 0.5) + W_E \cdot \boldsymbol{H}(U_{\text{currentRef}} - U_{\text{measure}}) \cdot (\boldsymbol{H}(V_{\text{measure}} - V_{\text{currentRef}}) - 0.5)) \quad (1)$$

The compared values are input to the Heaviside step function $H(x)$, which returns 1 when $x \geq 0$ and return 0 when $x < 0$. The results based on the same aspect are then multiplied with each other, indicating that the aspect is only satisfied when all related factors are measured to be qualified. As performing gait movements in a correct way is a necessary condition in each therapy goal, the score of efficiency is always multiplied by accuracy-related results. The output ***currentScore*** is normalized between −1 to 1.

As the difficulty levels progress, the reference values set at initial levels are likely to be out of reach for some patients in some exercises. For instance, the increasingly complex game scenes make it difficult for patients to maintain the same average walking speed V that they had at the initial simple levels. A generic solution is to assign another set of reference values at the most difficult level and fitting these values into a linear model, for interpolation:

$$V_{\text{currentRef}} = V_{\text{initalRef}} + (cl - 1) \cdot \frac{V_{\text{endRef}} - V_{\text{initalRef}}}{\text{endLevel} - 1} \quad (2)$$

It takes cl (current level) as an argument, seeking a relationship between the current reference value and reference values at initial level $V_{\text{initalRef}}$ and last level V_{endRef}.

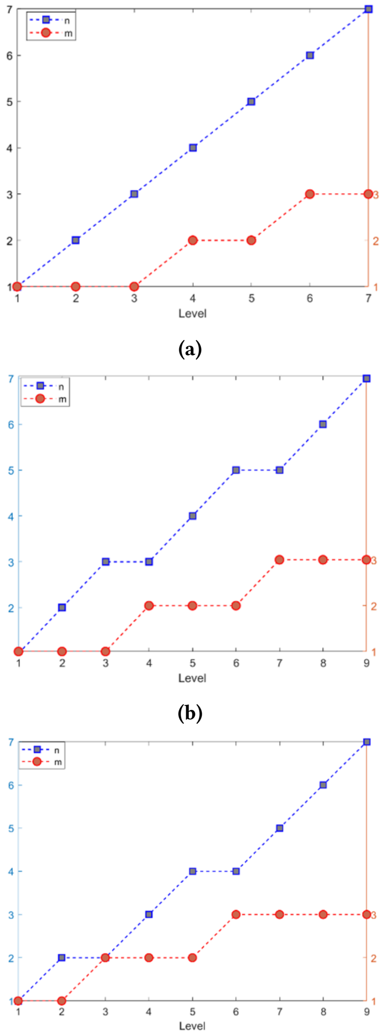
3.2 Difficulty adjustment

The other essential question on adaptation regards *how* to adjust the difficulty levels [15]. During gameplay, the difficulty decision module is responsible for updating the corresponding values of parameters for each task. Besides, as the goal of gait rehabilitation is to help patients regain their abilities to handle various walking scenes in real-life, it can be meaningful to provide physiotherapists a tool to influence the difficulty by integrating separate tasks.

Difficulty progression is here approached from a *transition* perspective, where all its relevant parameters are evenly increased (or decreased) either in parallel or in sequence:

- ***parallel progression scheme***: parameters can be increased simultaneously as shown in Figure 2.(a)
- ***sequential progression scheme***: parameters are increased alternately - one and only one parameter can be increased each time, shown in Figure 2.(b)-(c)

Having the choice of the two progression schemes helps physiotherapists to optimally serve diverse patients. For each task, the



(a)

(b)

(c)

Figure 2: Comparison between the two progression schemes: (a) Parameter trend example when the difficulty level progresses in parallel (M = 3, N = 7, T = 7); (b)(c) Two examples when level progresses in sequence (M = 3, N = 7, T = 9)

Algorithm 1: Tier calculation for difficulty-related parameters for *sequential progression scheme*

Input: Current level cl, and total tiers t_1, t_2 ... t_x of each parameter ($t_1 \geq t_2 ... \geq t_x$)
Result: The tier value of each parameter $v_1[cl]$, $v_2[cl]$ ... $v_x[cl]$ at current level
Init: $T \leftarrow t_1 + t_2 + ... + t_x - x + 1$;`// total levels`
incrList $\leftarrow$ []; `// parameters to be increased`
$v_1[1], v_2[1] ... v_x[1] \leftarrow 1$; `// starting value`
$randFlag \leftarrow 0$ `// necessity to add randomness`
for $i \leftarrow 2$ **to** x **do** $D_i \leftarrow \lceil T/t_i \rceil$; `// interval for increase of each parameter`
Function `ValueCalc`(cl):
  if $v_1[cl-1] \cdot v_2[cl-1] ... \cdot v_x[cl-1]$ *==0* **then**
    ValueCalc($cl - 1$) `// load previous value`
  else
    for $i \leftarrow 2$ **to** x **do**
      if $cl\%D_i == 0$ **then** incrList.Add(i);
      `// parameter` i `is ready for increase`
    end
    if *size(incrList) ==0* **then**
      $v_1[cl] \leftarrow v_1[cl-1] + 1$; $randFlag \leftarrow 1$
    else if *size(incrList) < 2* ***and*** $randFlag == 1$ **then**
      incrList.Add(1); $randFlag \leftarrow 0$;
      RandIncrease();
    else
      $randFlag \leftarrow 0$; RandIncrease()
    end
  end
  return
Function `RandIncrease`():
  randNum $\leftarrow$ incrList[RandomInt(1, size(incrList)) -1];
  $v_{randNum}[cl] \leftarrow v_{randNum}[cl-1] + 1$;
  incrList.RemoveAt(randNum);
  return

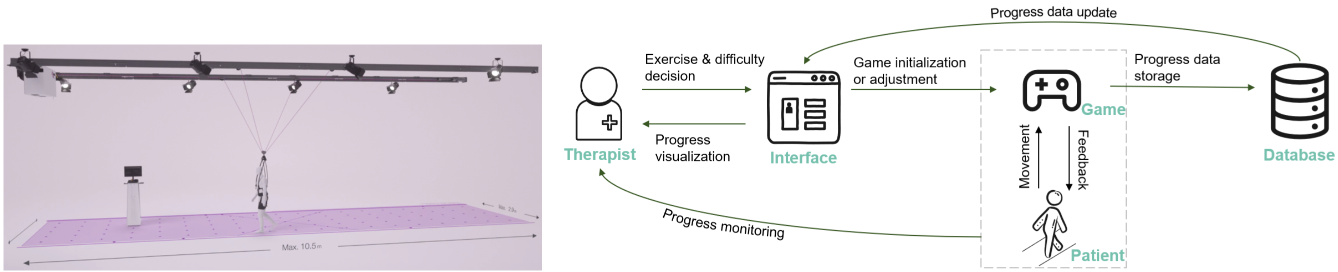
range and steps of each parameter can be set by physiotherapists. The ‘tier’ refers to the difficulty levels for each parameter.

During training, the values of each parameter are encapsulated and represented by integer ***cl*** for each task. It allows physiotherapists to understand and adjust the challenge level with a minimum cognitive effort.

Parameters are increased at a slower rate in a **sequential progression** scheme because then only one parameter can be increased each time. One benefit of sequence progression is to add more variety to difficulty adjustment. Every time the player enters a harder level, Algorithm 1 can randomly select which parameter to increase while ensuring the evenness, i.e. no parameter shall increase all the way to its maximum value. Although there can be multiple combinations of parameters at the same difficulty level, such a randomness will only occur when the level of difficulty increases; when it remain unchanged or decrease, the tier of each parameter remains unchanged.

An auxiliary method to the above two progression schemes consists of integrating different gait exercises into the same game level, thus increasing its difficulty. Naturally, it is the therapists who decide whether and how to integrate different tasks into the current level. To make this integration process smoother, several design principles are proposed, aiming at getting the integrated levels balanced. First, based on clinical experience, the integrated task(s) should have an overall lower challenge level. This will not only prevent patients from exhaustion by attempting combined actions that are far beyond their current ability, but also give them a chance to review and consolidate basic gait movements.

Second, the difficulty progression for the integrated task(s) should be less demanding (e.g. deciding which task can be kept at a level



(a) Setup of the RYSEN system **(b) Functional diagram**

Figure 3: Global architecture of our prototype system

where the patient is already proficient). Last but not least, this combination of separate gait tasks should resemble real-life challenges as much as possible, to promote motor knowledge transfer.

3.3 Level generator

The values of parameters, and possible integration information derived from the difficulty decision module (see Figure 1), are applied in the generation of game levels. In contrast to hand-crafted methods, our PCG-based method is able to assist physiotherapists in flexibly generating levels in real-time, as well as bringing useful variation to gait training.

The goals of gait rehabilitation vary depending on the patients' conditions and recovery phase, which can include muscle strength improving, steady-state gait, gait adaptability, dual-tasking, etc [24]. Usually, each goal encompasses several related sub-goals as concrete tasks for patients to accomplish. To provide a targeted rehabilitation, these tasks are then mapped into the movement challenges embedded in game level design, responsible to guide and motivate patients to adhere to them.

Dividing a long-term rehabilitation process into small pieces of achievements is a good way to maintain patients' motivation. The length chosen for each level segment is another prominent property input to the level generator: it can be either restricted by physical conditions or set by therapists.

4 PROTOTYPE IMPLEMENTATION

This section describes our implementation of a standalone prototype that makes use of the aforementioned adaptation scheme. It first introduces the prototype components, and then focuses on the game content generation, as well as on how to steer the generation process. To better support physiotherapists during a training session, the evaluation of the patient's performance is logged and visualized through a graphical user interface.

4.1 Prototype overview

We adopted the RYSEN rehabilitation technology [22], a three-dimensional overground body weight support (BWS) system. As shown in Figure 3a, it provides a rectangular space that ensures a flexible and natural walking experience. The active mechanisms used for both horizontal and vertical movement of the patient can prevent falling while not causing excessive accelerations, thus lowering the risk of hurting the patient. Moreover, the RYSEN can measure the trajectory of a patient with minimal tracking errors at BWS mode [22]. Therefore, the patient's position and orientation can be tracked without wearing additional sensors.

The main components of the prototype and their interrelations are depicted in Figure 3b. To start a gait exercise, the therapist first selects a therapy task for the patient through the interface. The patient's progress data per task is stored in the database and visualized. Based on the therapist's experience, the starting difficulty level for the selected exercise is chosen.

The game system can adjust the difficulty autonomously based on the collected information and player model. In addition, therapists may need to modify the difficulty level at any point during training, based on their own observation or the patient's performance. To better support such manual control and intervention, timely adjustment options are provided.

4.2 Design of the level generator

Two therapy goals are targeted in this implementation, which are gait adaptability and dual-tasking. Gait adaptability is defined as the ability to adjust the gait pattern to adapt to different walking environments. Dual-tasking is meant to help patients avoid the so-called dual-task interference [1], which usually happens when performing two tasks simultaneously. Both therapy goals can be further divided into a series of concrete tasks. For instance, slalom walking, obstacle avoidance, and sidewards walking tasks can stimulate gait adaptability. As for dual-tasking, memorizing while performing actions is a typical example of a clinically meaningful goal.

For immersive interaction between the patient and the game, we use floor projection. Such an immersion mode not only can make full use of the whole workspace of the RYSEN but has also the advantages of flexibility and scalability. The game presents a top-down 2D view on the level, and the environments are nature-related. Abundant nature-related metaphors inspire various scenes according to the different clinical goals. Besides, a nature-related setting has the potential to cater to a wider range of patient's age, gender, personality, and cultural background [20]. Both the game design for each task and the corresponding movement challenge generation are described in Table 1. Game elements are laid out with clear clinical purposes and in a parametric manner.

Tasks	Gameplay movements	Movement challenge generation
Slalom walking	A path in a sinusoidal layout is generated. The player should stay on the winding road when walking from start to end. Parameters including the path **width** and **randomness** (in amplitude and frequency) affect the difficulty level.	Compute a list of points along the path's centerline. Based on this, calculate the position of path vertices and generate the triangle mesh for the path. Construct collision area based on derived vertices and triangles and apply textures.
Obstacle avoidance	Static flowers and moving insects act as obstacles along the path. When walking on the path, players should avoid them. Three parameters, including the **size**, the **number** and the moving **speed** of the obstacles characterize the difficulty.	Place obstacles along the path. The distance between consecutive obstacles should be greater than the visual outline of the patient.
Sidewards walking	A patient is guided to mimic a crab's way of walking. By moving sidewards with the crab to the end on the segment, the patient will win a shell as a gift. Both **width** and **length** of the path affect the difficulty.	A crab is spawned in front of the patient at the beginning. A stone path is generated on the beach, with the given width and length from start to end.
Memory	In the forest, a patient needs to find out the animal behind each tree and remember it. He/she succeeds in the level by finding all pairs of trees with the same animal. The number of **pairs** can be adjusted to change the difficulty.	A matrix storing all positions for placement is built. Pairs of animals are then place based on random shuffle. All animals are hidden behind a tree and will only show up when the patient walks onto it.

Table 1: Mapping from four separate therapy tasks to gameplay movements and generation details

4.3 Adaptive steering of the level generator

The prototype assesses the patient's performance based on the aforementioned player model and adjusts the difficulty level by applying the parameter progression schemes and level integration strategy.

A level is usually divided into several sections. In each section, there are two rest zones and one training zone in between; see Figure 4. Rest zones indicate the start and end, and are used to provide feedback on previous performance. Between two rest zones, there's a training zone, where the patient performs movements by interacting with the game elements. The patient interacts with the game elements on the training zone. At the same time, the system keeps track of the patient's movement data, for player model and subsequent level generation purposes.

To illustrate the two parameter progression schemes, we take an example of difficulty adjustment of slalom walking in two different ways based on the player model. A typical evaluation form for slalom walking is shown in Table 2, based on both accuracy and efficiency aspects.

The off-road time factor F refers to the frequency that a player walks out of the road and the off-road duration percentage P indicates the percentage of duration the player spends outside the road to the total time. As the road gets irregular and narrower, the

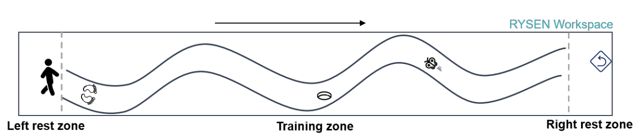


Figure 4: The RYSEN workspace and the three zones used

Evaluation aspects		Accuracy		Efficiency
Factors		Off-road times F	Off-road duration percentage P	Average speed V
Reference values	Initial values	1	10%	0.7 m/s
	End values	Remain unchanged		Decreases 15% (i.e. 15% $\times$ 0.7)
Recommended weights		0.65		0.35

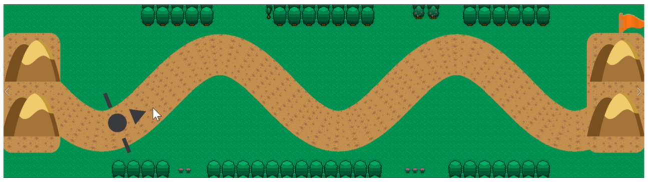
Table 2: Evaluation table for slalom walking task

reference value of V can be harder for patients to balance accuracy and efficiency. Hence, the predefined reference value is made difficulty-related (see Equation 2).

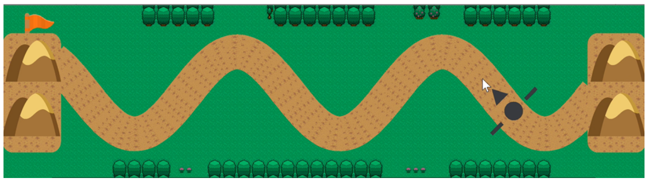
A decision of the range and increment of two parameters (either by the system or by the physiotherapist) could be as follows:

- **road width** (8 tiers): ranges from 0.3 (i.e. visual diameter of the patient) to 1.0 meters, in 0.1 meters increments
- **randomness** (4 tiers): ranges from no randomness, to randomness in amplitude, then to randomness in frequency and, at last, to randomness in both

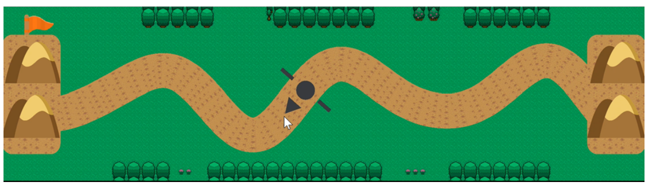
The progression of the two parameters with different schemes is illustrated in Figure 5. At the beginning, the path has a width of 0.7 meters with a regular shape (Figure 5a). With the sequential progression scheme, every difficulty improvement only increases



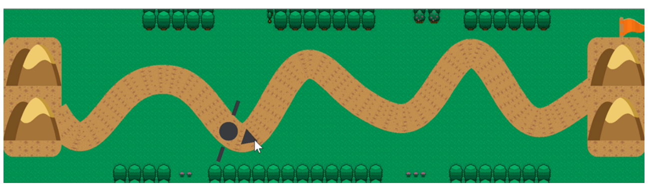
(a) 0.7**m wide, regular path**



(b) 0.6**m wide, regular path**



(c) 0.6**m wide, randomness in amplitude**



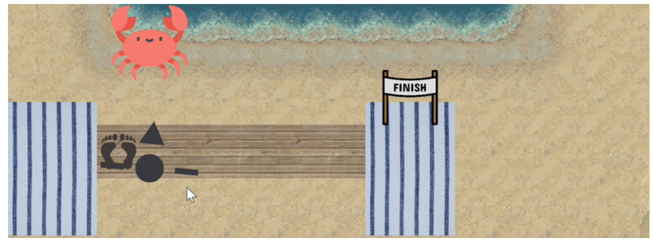
(d) 0.5**m wide, randomness in amplitude**

Figure 5: Difficulty progression with different progression schemes: (i) Sequential progression scheme: (a) → (b) → (c); (ii) Parallel progression scheme: (a) → (c) → (d).

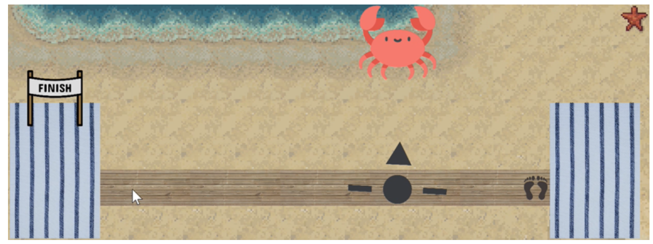
the tier of one parameter. In the next level, the *roadwidth* parameter is first decreased by 0.1 meters (Figure 5b). If the performance keeps increasing, the *randomness* factor is then raised to tier 2, in this case, applied to the slalom amplitude (Figure 5c). In short, with the sequential progression scheme, the slalom level follows the sequence from (a) to (b) and then to (c).

By contrast, a parallel scheme increases the parameters when they are both eligible to be increased (as from (a) to (c)). Otherwise, only the eligible parameter is manipulated (e.g. *roadwidth*, from (c) to (d)).

The two difficulty progression schemes can be easily altered to support more gait tasks. Take sidewards walking as an example, which requires asymmetry effort for the lower limbs. Consider that the target group who suffers from gait impairment can have different conditions in each leg, the adaptation can be applied for each direction separately. And assume a patient starts the sidewards walking exercise with the same difficulty for both directions. Due to the worse condition in the right leg, the patient walks slow and sometimes fails to continue moving sidewards. As a result, a separate difficulty adjustment is then computed and applied to each



(a) *roadwidth*: 0.8**m**, *roadlength*: 4**m**

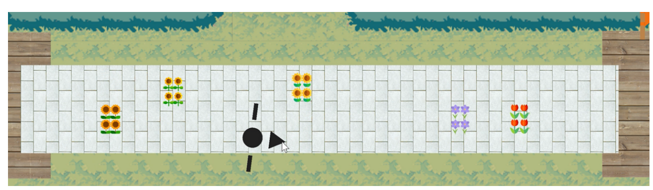


(b) *roadwidth*: 0.5**m**, *roadlength*: 7**m**

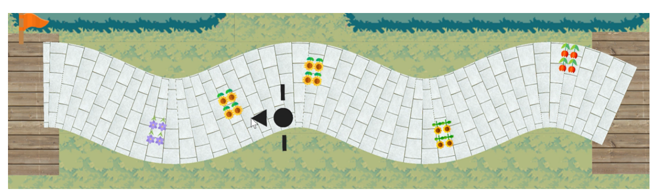
Figure 6: Sidewards walking levels for customized (a) right walking and (b) left walking, after deriving separate difficulty adjustment over several rounds.

direction separately, so as to provide suitable training for either leg, as depicted in Figure 6.

As mentioned before, in the context of gait rehabilitation, dual-tasking combines two different (movement) tasks into one single challenge, which is another way of increasing the difficulty; after all, walking on a non-straight road while avoiding obstacles is not rare in daily life. For example, combining slalom walking and obstacle avoidance has increased difficulty as well as helps acquire obstacle avoidance skills, within a new challenging scenario, as shown in Figure 7.

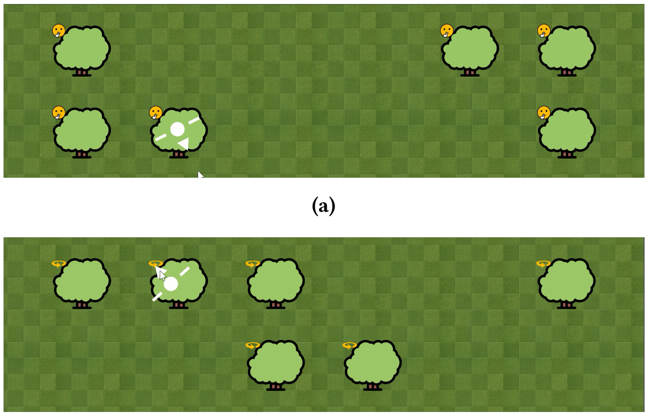


(a)



(b)

Figure 7: Obstacle avoidance scene: (a) standalone level (b) integrated level



(a)

(b)

Figure 8: Memory task examples: (a) as a standalone task; (b) as a dual-task, integrated with turning around

One last example of task integration implemented in our prototype consists of combining a memory task with a turning around gait. As described in Table 1, the separate memory task simply consists of finding the pairs of animals hiding behind trees, as shown in Figure 8a. For the task integration, the turning around movement was encoded in the game as 'turn around the tree to find out the animal behind it'. This requirement is indicated next to the tree, by a rotation symbol, as shown in Figure 8b.

5 EVALUATION

To assess the extent to which PCG-based adaptive gait rehabilitation supports physiotherapists in achieving their target outcomes, we evaluated our approach using the implemented prototype. This section summarizes the evaluation process and its outcome, with a special focus on two aspects: (i) the diversity this approach brings into gait rehabilitation, (ii) the usefulness of automatic difficulty adjustment schemes for different tasks.

5.1 Method

The participant group was composed of physiotherapists with experience in gait rehabilitation. For therapists with less knowledge in the RYSEN setup, an introduction session was given at the beginning. Because it was logistically unfeasible to meet each therapist face-to-face to physically evaluate the game prototype, we devised an alternative way of evaluating it, in the form of prerecorded play-through footage and subsequent questionnaires. This method has several advantages: it gives physiotherapists a clearer focus, and is independent of their game playing experience. Above all, without the concern of a patient to take care of in real-time, physiotherapists are thus free to concentrate on the procedural levels as well as on the gameplay itself, e.g. how fair the evaluation of the player's performance is, how smooth the difficulty transition between two levels is, etc. The gait tasks used in the evaluation included slalom walking, obstacle avoidance, sidewards walking, as well as a memory task (see Table 1).

The evaluation was divided into three phases, aimed at investigating the *quality of generated levels*, *adaptivity usefulness*, and *effectiveness of the control provided to the therapist*. The complete questionnaire in full detail is provided as supplementary material to this paper (and can also be found elsewhere).

At the beginning, an introduction text and an explanatory video were presented to participants. The text described the RYSEN setup, project background and goals, and the focus of this evaluation. The video further introduced the basics of the game mechanics, the avatar representation of the player, etc.

The first part focused on the *quality of generated levels* for each task. Physiotherapists, by watching the interaction between the avatar and different game elements, were first asked whether the tasks in the game could stimulate the desired gait movement. A series of generated levels with the same values for difficulty-related parameters were shown, and participants were asked (i) if, based on their experience, these PCG-based levels were perceived with comparable difficulty, and (ii) to which extent they could bring helpful diversity into rehabilitation.

Next, the evaluation focused on the *transition between difficulty levels*. To make the evaluation session compact, instead of showing long-term and repetitive gait training, the measurement of player skills and critical difficulty adjustment steps were presented. Firstly, three exercise scenarios in slalom walking were displayed, where the patient (i) walked out of the road frequently, (ii) kept on the road but at a slow pace, and (iii) kept on the road at a good speed. Based on accuracy and efficiency aspects, the system evaluated the performance and visualized the scores. Physiotherapists were then asked to rate the evaluation scheme. Secondly, the working of the two difficulty progression schemes was assessed. Starting from level x, the patient showed proficiency in the current task and the difficulty level was increased twice, in parallel and sequence, respectively. Participants were asked about the appropriateness of the chosen difficulty increase for each progression scheme. After that, they were asked about the extent to which the two progression schemes were suitable to adapt to patients with different conditions.

The evaluation of *task integration* was carried out by comparing the difficulty between levels for standalone tasks and for integrated tasks. For this, they were presented integrated obstacle avoidance with slalom walking (as in Figure 7) as well as turning around with memory task (as in Figure 8). Apart from the perceived differences in difficulty, participants were also asked to rate the variety that such integration brings to difficulty adjustment. Finally, sidewards walking was also assessed as a special task regarding difficulty adjustment, as it may challenge differently left and right lower limbs. Accordingly, the task difficulty was adapted separately according to the patient's performance in each direction. Participants were then asked to assess the usefulness and versatility of such asymmetric difficulty adjustment in gait rehabilitation.

In the last part, the evaluation assessed if the interaction scheme provided was *helping physiotherapists master the rehabilitation process*. This included session status information, data on patient performance, and direct control options for difficulty adjustments. Participants were asked to rate the information provided through the interface as well as their satisfaction with its control options.

5.2 Results and analysis

We collected valid feedback from 9 physiotherapists. To start with, the functionality of mapping from therapy goals into gameplay actions was recognized. The average score of the four game level designs was 4.25, where 5 means the game level very much satisfies the physiotherapist's expectations of what the patient should do to fully complete each corresponding goal. Figures 9 and 10 summarize physiotherapists' answers about the diversity and balance of our procedurally generated levels.

Overall, the randomness brought in by PCG was considered by physiotherapists a very valuable contribution to gait rehabilitation, the more so when the game mechanics involved richer game design elements (e.g. with obstacle avoidance and memory tasks). Moreover, this diversity was not achieved at the expense of balance, as over 75% of participants agreed that the levels presented for each subgoal shared similar difficulty.

Regarding adaptation, the prototype first assesses a player's performance for a while, to decide whether difficulty needs adjustment. Nearly 90% of participants agreed that performance based on efficiency and accuracy is clinically desirable. In their additional written comments, some participants mentioned their wish to separately select aspects (e.g. only accuracy or efficiency), as well as set the velocity range for the task.

When switching challenge levels, the sequential progression scheme was regarded by participants as a better choice, as shown in Figure 11. According to their comments, having uniform difficulty increments between adjacent levels is an advantage. However, this is not necessarily always the case: some physiotherapists expressed that, for some patients, they would like to apply a parallel progression strategy to make it more challenging. This is reflected by the additional fact that participants agreed with the statement 'The choice between the two progression schemes is convenient to adapt to patients with different conditions', with the mean score over 4.5.

As shown in Figure 12, over 83% of participants agreed that the integration of therapy tasks can bring helpful diversity to the difficulty adjustment. However, participants' concerns about possible dizziness caused by 360-degree turn incidentally affected the results. In participants' suggestions, other movements such as squatting, 180-degree turn are considered good alternatives.

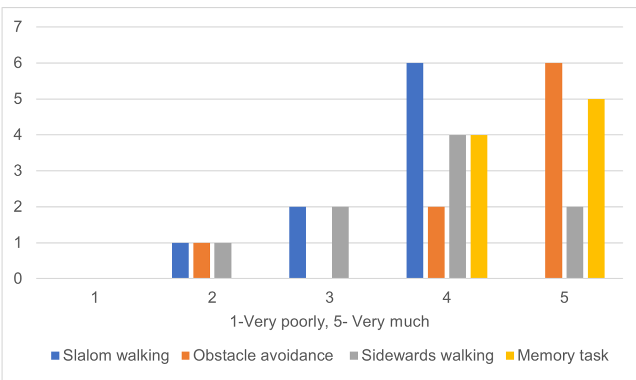


Figure 9: Replies to '*To which extent is the diversity of the exercises shown helpful for patients to accomplish each corresponding therapy goal?*'

Figure 10: Replies to '*To which extent are the exercises shown for each therapy goal perceived with similar difficulty based on your clinical experience?*'

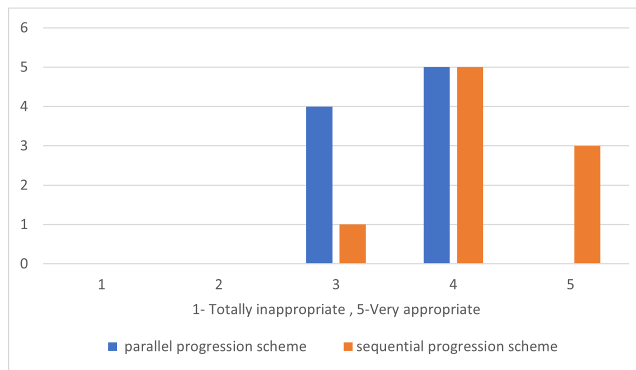


Figure 11: Replies to '*From the three levels shown above, how appropriate is the corresponding scheme to adjust the therapy goal difficulty for patients?*'

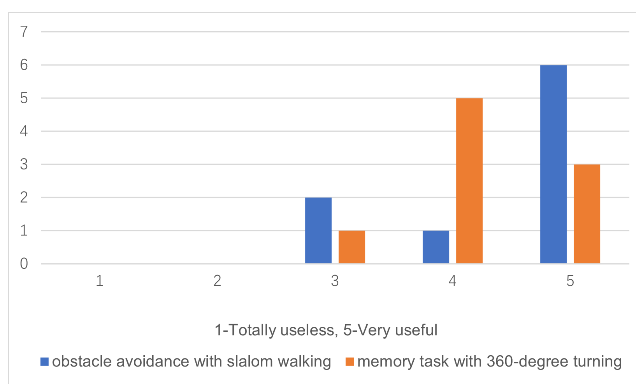


Figure 12: Replies to '*Through comparisons, how useful do you think such integrations are to bring variety to difficulty adjustment?*'

Adjusting difficulty separately for left and right sidewalking was considered to be sensible and useful by nearly 70% of physiotherapists. Participants who rated a lower score for such a strategy commented they preferred a symmetric training. Therefore, it might be wise to provide both symmetric and asymmetric difficulty adjustment, and let physiotherapists decide which to apply, based on their experience and on the patient condition.

Finally, all participants gave positive feedback on the data gathered and displayed about the patients' performance, as well as about the control options for tailoring the difficulty levels. Although they were not able to perform hands-on trials with their patients in a clinical setting, these results indicate that the designed interaction between the automated challenge generation system and the therapists is considered rather useful and empowering.

6 CONCLUSION AND FUTURE WORK

In this paper we showed that adaptive gait rehabilitation based on procedural content generation (PCG) can effectively support physiotherapists in achieving customized outcomes. We proposed a generic adaptation scheme that steers a procedural generator of gait challenges. A player model based on a patient's accuracy and efficiency, is used to steer the challenge level generator. The weights of accuracy and efficiency can be flexibly adjusted to the characteristics of different therapy needs and tasks. Two generic parameter progression strategies, sequential and parallel, were proposed to dynamically adjust difficulty as the patient performance evolves. Such difficulty adjustment strategies can be fine-tuned by therapists to fit specific gait rehabilitation tasks, e.g. when they require to distinguish, for a given task, asymmetric efforts of left and right lower limbs. Moreover, integrating different therapy goals in a meaningful way can also steer the level of difficulty, as well as bring in variety to the challenges presented.

Our design, aimed at the RYSEN overground setup, was implemented in a standalone prototype system, which was evaluated by a group of physiotherapists. The variety of in-game generated levels was considered very helpful and appropriate to achieve the stated therapy goals. In addition, for a chosen difficulty, our method is able to present abundant variation of level layouts with a comparable challenge degree for the task at hand. Moreover, physiotherapists can directly customize task difficulty in real-time, either by issuing a desired adaptation or by combining one therapy goal with another. This integration, often deployed in clinical settings, was also considered to bring in useful variety into difficulty adjustment.

Considering that rehabilitation goals and schedules may widely vary per patient, it is up to physiotherapists to decide which adaptation strategy to apply, and when to revise it, intervening to adjust the difficulty. For this, physiotherapists are conveniently served by the patient performance data, the control options and the degrees of freedom provided by a system like the one described in this paper.

Our generic adaptation scheme is suitable for supporting physiotherapists in a wider clinical context, beyond the demonstrated gait rehabilitation in the RYSEN setting. On the one hand, multi-parameter progression strategies can purposefully steer the difficulty of a variety of challenges. On the other hand, the performance data of each patient as well as the control options provided to physiotherapists can lead to the generation of more personalized levels. Such benefits can be realized whenever (i) the difficulty-related parameters are properly defined according to each clinical purpose, and (ii) the evaluation factors and values, chosen in collaboration with physiotherapists, accurately depict player performance. In all cases, PCG can fulfill its supporting role for any feasible size of the (physical or virtual) game space available, as long as the layout of each level segment being generated is sensibly designed. Moreover, when needed, different mechanics can be combined to generate clinically meaningful levels, as we have also exemplified.

Currently, the adaptation is implemented within the horizon of single rehabilitation subgoals. In the future, the duration proportion of each subgoal could be made flexible [12]. For example, if a patient is measured to perform well in the first task in the early stage of today's training, the system could propose to spread the rest of their time over the remaining tasks. Moreover, the rehabilitation period for each therapy goal could also be adapted, so that the accumulated performance of the patient over its various subgoals could lead the system to propose extending or reducing the treatment duration. For example, by monitoring how the performance of one specific goal is improving, the system could propose that the patient only needs such training for two weeks instead of three weeks.

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