Probabilistic Modeling and Verification of an Adaptive VR Serious Game for Patients with Cognitive Impairment

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Abstract. Serious games proved to be an effective tool for screening cognitive deficits and aiding in the diagnosis of neurodegenerative diseases like Alzheimer's and Parkinson's. Additionally, they are recognized for their benefits in cognitive training. In this work, we introduce a new serious game targeting inhibitory control, a cognitive function often impaired in Alzheimer's and Parkinson's patients. The specificity of this game is proposing an inhibitory control task in immersive virtual reality with adaptive difficulty adjustment based on the patient's performance. After modeling the game as a Discrete Time Markov Chain, we use the probabilistic Model Checker Prism to verify the model with respect to some crucial dynamic properties and to retrieve the probabilities associated with some classes of paths describing the patient's gameplay. This formal approach aims to support the medical staff in spotting the differences between expected and observed behavior.

Keywords: Probabilistic Modeling · Model Checking · Serious Game · Adaptive Difficulty · Virtual Reality · Neurocognitive Disorder

1 Introduction

Neurodegenerative diseases like Alzheimer's and Parkinson's often impair cognitive functions, requiring early detection and regular monitoring. Traditional diagnosis relies on neuropsychological and biomarker tests, which are time-consuming for clinicians and patients. Researchers are exploring quick, objective behavioral markers to complement standard assessments and support early detection. Serious Games (SGs), which are video games for serious purposes [11], are more appealing among elderly patients compared to traditional exercises [3] and show promise in improving cognitive abilities [10].

DSM-5-TR [2] describes cognitive impairments (CI) as cognitive and behavioral disturbances that impact daily functioning and categorize them into mild Neuro-Cognitive Disorder (mild NCD), where autonomy is retained but supervision is needed, and major NCD, which significantly impairs independence.

Fig. 1. Example of SG gameplay. The rule is to throw red balls into the container and black-dotted ones away. The user interface displays the player's score and mistakenly thrown NoGo-Balls (marked with red crosses) on the left, and ranking on the right.

This work presents an immersive Virtual Reality (VR) SG designed to enhance Inhibitory Control (IC), the ability to regulate attention, behavior, or emotions to suppress impulses or distractions and respond appropriately [1]. VR immerses users in a computer-generated environment, typically through a headset, enabling realistic interaction and enhancing the sense of presence [5]. The effectiveness of VR-based training depends on factors such as fidelity, engagement, interactivity, and sensory involvement [6]. Our SG, shown in Fig. 1, is based on the Go/NoGo Task [4], where participants perform an action in response to certain stimuli and inhibit that action for others. In our implementation, players throw balls into a basket when the ball matches an active rule (Go) and onto the floor when it does not (NoGo). To support players in reaching the flow state (i.e., a deeply focused and immersive state of engagement [9]), the SG dynamically adjusts its difficulty based on the player's performance.

We model the SG as a Discrete-Time Markov Chain using PRISM [7]. To reflect varying gameplay scenarios, we assign probabilities to key actions based on the patient's CI stage (healthy, mild NCD, or major NCD) using *a priori* weights from medical experts. PRISM is used to verify temporal properties and compute the likelihood of key gameplay paths. While previous work has applied PRISM to SGs [8], our approach is novel in modeling a game that dynamically adapts to the player's performance. The developed PRISM code and query evaluation are available on GitHub[3].

2 Proposed SG and its Prism Model

In the developed SG, players should throw balls into the front basket (Go-Basket) if the ball matches the active rule (Go-Ball) or onto the floor (NoGo-Basket) if it does not (NoGo-Ball). Figure 1 shows an example where only red balls should be thrown into the Go-Basket. The game ends if the player exceeds the allowed number of NoGo-Balls in the Go-Basket (MaxNoGoInGoBasket) or if the number of unthrown balls exceeds the table limit (MaxBallsOnTable).

[3] https://github.com/AlessandroForgiarini/InhibitoryControlSGModel

A match consists of a fixed number of TotalGameSessions, each lasting SessionDuration seconds. After each session, the Game Manager adjusts difficulty (LevelIncrement) based on the PlayerScore, which reflects both throw accuracy and the proportion of time with few balls available to throw on the table (FewObjectsOnTableLimit).

The Game Manager adapts the difficulty by increasing it if PlayerScore exceeds IncDiffBound, decreasing it if below DecDiffBound, and remaining unchanged otherwise. The game has three difficulty levels, adjusting TimeToGenerateBall from 5 seconds (easy) to 3 seconds (hard). Each ball has a predefined probability of being a Go-Ball or NoGo-Ball. All parameter values were set based on medical consultations and pilot testing.

2.1 Representation in the Prism Language

The model simulates a 20-minute game match and is structured into three modules, each managing a different aspect of the SG. The **Manager** tracks session progress and adjusts difficulty based on predefined rules. The **Gameplay** represents each session, managing Go/NoGo balls, timers for ball generation, and tracking the time with few balls available to throw. The **Patient** models the player's responses, including correct and incorrect throws, recovery time, and the possibility of ending the match early.

Each transition in the global model (across all modules) represents one second of gameplay. Only one command can execute at every state, ensuring deterministic behavior and eliminating non-deterministic transitions. Each module has local variables representing the SG state and commands defining its behavior.

The flow starts by resetting the session counter, setting the initial difficulty, and starting the first session. Commands are mutually exclusive and sequential: after each execution, guards are reevaluated to determine the next valid action. Guard evaluation follows the SG logic: i) check if the player lost the game, ii) execute a throw if possible, iii) generate a new ball, and iv) update timers.

2.2 Patient Parameters

The player's behavior in the game match simulation is driven by probabilities encoded in the model, determining the likelihood of specific transitions when conditions are met. These probabilities influence the chances of making a correct or incorrect throw (Go or NoGo), the required recovery time before throwing again, and the likelihood of ending the game early. Recovery time can be: fast (immediate readiness to throw); normal (3-second rest); slow (6-second rest). The probability of premature game termination accounts for both technical issues and the player's decision to stop due to fatigue or loss of interest. To estimate these probabilities, we consulted seven doctors experienced with IC disorder at the CoBTekLab[4] who provided us with probability estimates for each CI level.

[4] https://univ-cotedazur.fr/laboratoires/cognition-behaviour-technology-cobtek

3 Probabilistic queries and results

Based on the patient's disease level, as reflected in the probabilities introduced in Subsection 2.2, three different models were constructed since some transitions are not possible when these probabilities are zero. Model construction and query execution were done using PRISM on a desktop computer with an AMD Ryzen 3700X processor and 32GB RAM @ 3200MHz. We defined probabilistic queries to validate the model and analyze how gameplay evolves based on the patient's disease level. For conciseness, we present key queries that cover different model aspects, with full results accessible on GitHub.

Queries 1 and 2 ensure the model behaves as expected and is independent of the patient's properties; any dependency would suggest an encoding error. Queries 3 and 4 assess how patient behavior changes with disease progression, using PRISM rewards to calculate the average number of states where specific conditions are met before the match ends.

Query 1 What is the probability of reaching the final state of the model? This query checks whether the model ensures that all scenarios eventually lead to the final state. If the probability is below 1, there is a chance the final state will never be reached.

Query 2 What is the probability of throwing a ball when one is available? This query checks that in every valid state (i.e., when the patient is playing, a ball is available, no throw is in progress, and the patient's time to recovery is zero), the next will be one where a throw is made. If the probability is below 1, it means that sometimes the patient will not throw the ball when able.

Query 3 How long will the patient play on average? This query estimates the average playtime for a patient during a game match.

Query 4 How many times will the game difficulty be reduced? This query estimates the average number of times the Manager will decrease the game difficulty during a match.

4 Discussion and Conclusions

This paper expands on the use of a SG combined with theoretical modeling and verification of both the game and patient behavior to support doctors in diagnosing levels of CI.

Queries 1 and 2 confirm the model behaves as expected. Behavioral queries (3 and 4) show that healthy individuals tend to play for 6–7 minutes, mild NCD patients for 4–5 minutes, and major NCD patients for only 2–3 minutes. Additionally, difficulty adjustments occur more frequently for patients with CIs, indicating the SG adapts to their needs. These probabilistic results highlight distinct behavioral patterns among the three groups, suggesting the tool can help clinicians assess disease stages. For example, if a healthy person plays like a mild NCD patient, the model can detect the inconsistency. This also enables game personalization based on patient profiles.

The current model, built on a simplified 3-level SG, demonstrates feasibility. A more complex version is in development, including additional difficulty levels and color combinations. The results will be refined in collaboration with medical experts and used to perform a future user study with real patients with CI to validate and improve the model's accuracy.

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