Improve Your Gait With Laboratory Agent

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***Abstract*—Gait analysis is fundamental in injury prevention and physical performance improvement, which raises the need to automate this process and generate personalized recommendations. In response, we propose the design of a gait laboratory agent, developed under the principles of systems thinking, cybernetics and artificial intelligence. This agent incorporates causal diagrams to facilitate its understanding, as well as algorithms that allow system feedback, encourage autonomous learning and reduce the influence of chaos in decision making.**

***Index Terms*—Gait, Gait laboratory, DQN, System, cybernetics, artificial intelligence, recommendations, feedback loops.**

I. INTRODUCTION

Human gait is a fundamental and complex motor activity. From a very early age, humans develop the ability to move on two feet, and as they grow, they master it to the point of running at high speeds or walking for long periods of time. Despite being a common everyday activity, gait is governed by complex interactions between musculoskeletal, neurological, and environmental factors. Even though it is an everyday activity, the way we walk cannot be overlooked, as it can be an indicator of health status and biomechanical efficiency. Abnormal gait patterns can reveal underlying pathologies, neuromotor deficits, or mechanical imbalances, making gait analysis an essential tool in clinical diagnosis, rehabilitation, and athletic performance.

From a biomechanical perspective, human gait can be conceptualized as the dynamic behavior of a system with multiple degrees of freedom (multi-DOF) check in [5]. The human body, composed of interconnected joints and segments, behaves in a coordinated manner to achieve stability and forward progression. With this, we can consider walking as forward movement in an upright position, while weight is distributed between one of the legs and the floor is not left; as mentioned in [2]. And in which, the independent behavior of different parts of the body such as: the hips, knees, feet, ankles, etc., construct walking.

Traditional gait laboratories use motion capture systems, force plates, and electromyography to assess both kinematic (position, velocity, acceleration) and dynamic (forces, moments) variables [1]. While these systems provide high-fidelity data, they are often costly, location-dependent, and require expert interpretation. This creates a barrier to widespread implementation in community health or personal training environments.

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To address these limitations, we propose the design of a software-based intelligent agent that emulates the core functionalities of a gait laboratory, integrating biomechanical modeling with systemic thinking and artificial intelligence principles. Instead of treating gait as a static event, we approach it as an adaptive system influenced by internal states (e.g., fatigue, muscle coordination, previous injuries) and external factors (e.g., environment, sensor accuracy, user habits). By leveraging feedback loops and causal modeling, the agent aims to continuously learn from user data, refine its predictions, and deliver personalized recommendations.

This approach aligns with the cybernetic notion of self-regulating systems, where the agent not only perceives but also adapts its decision-making in response to feedback. In doing so, it incorporates elements of chaos theory to manage variability and uncertainty in human movement, which is inherently nonlinear and sensitive to initial conditions.

The proposed system architecture focuses on modularity and feedback. It includes modules for data acquisition (via sensors), preprocessing and storage, inference through an adaptive engine, and validation by a specialist. The integration of causal diagrams and simulation environments supports both conceptual understanding and implementation testing.

On the other hand, a widely accepted abstraction of this dynamic is the inverted pendulum model, which describes how the body propels itself over the supporting leg during walking. This simplified model helps to understand the mechanisms of energy conservation and postural control, but walking in the real world requires more advanced representations that take into account limb coordination, muscle activation, and external disturbances. Unlike the simple model, the dual model includes both the support leg and the swing leg, allowing for a better capture of the dynamics of actual walking, especially during double support and the transition between steps. Furthermore, in real-world environments, the system must adapt to uneven terrain, obstacles, changes in speed, or slopes. More complex models include adaptive and learning responses that the pendulum model cannot cover.

II. Methods and Materials

The development of the gait laboratory agent followed a systems science perspective, which offers a robust framework for modeling complex and dynamic systems. This methodology facilitated the identification of feedback loops, nonlinear dependencies, and key elements affecting gait and rehabilitation. Principles of systems thinking guided the overall design, enabling an integrated view of patient, data, and decision-making interactions.

A high-level system diagram (Figure 1) was developed to visualize the system architecture. It outlines core components such as data acquisition modules, storage, decision logic, and communication with external actors like patients and specialists. This helped clarify the information flow, pinpoint interdependencies, and locate opportunities for adaptive behavior.

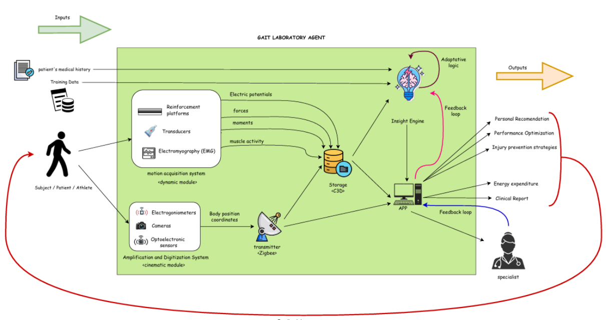

Fig. 1: System diagram

To understand internal dynamics and influence pathways, a causal loop diagram (Figure 2) was developed. This representation emphasizes the dynamic feedback nature of the system, showing how elements such as fatigue, adherence, and environment can interact over time and impact outcomes.

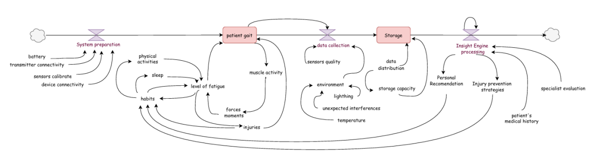

Fig. 2: Causal loop diagram

To evaluate the proposed agent, a simulation-based approach was adopted. Given the absence of physical infrastructure, a custom environment was created using Gymnasium to replicate a virtual gait lab. This included modeling simulated patients with clinical and biomechanical characteristics, represented by structured state vectors. These states encoded variables such as joint mobility, muscle strength, balance, and gait speed, and were generated using domain-informed rules to preserve realistic patterns and dependencies.

A Deep Q-Learning (DQN) agent was implemented to learn optimal intervention policies over time. The reinforcement learning setup enables the agent to adapt its decisions through iterative feedback, guided by a reward function. The reward structure is outlined in Table 1, designed to incentivize accurate recommendations aligned with the simulated patient's condition.

TABLE I: Reward Structure for Gait Agent

Action Outcome	Reward
Correct Recommendation	+1.0
Incorrect Recommendation	-0.1
No Ground Truth Available	0.0

To model the full decision cycle, a discrete-time interaction loop was simulated. Each episode represented a patient encounter in which the agent receives a state, selects an action (recommendation), and updates its policy based on reward feedback. A memory buffer stores experiences for learning stability, and simulation episodes are logged for evaluation and policy refinement.

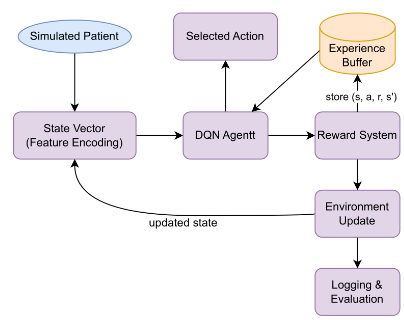

Fig. 3: Reinforcement Learning Workflow Diagram

To enrich the diversity and realism of the simulated patients, a simplified Degrees of Freedom (DOF) model was introduced to emulate different gait behaviors. This abstraction allows variation in joint dynamics, balance, and postural control. By incorporating this into the environment and training process, the agent was exposed to a more diverse set of biomechanical conditions, increasing its generalization capability. Training with DOF-based patients encouraged the agent to learn policies that are robust across a range of movement limitations and rehabilitation needs.

This framework enabled iterative experimentation to test the agent's adaptability, learning efficiency, and policy generalization. It aligns with digital health objectives by supporting personalized interventions and continuous improvement through simulation. By combining structured simulation, system modeling, and reinforcement learning, the proposed solution offers a scalable and robust method to support clinical decision-making in gait rehabilitation environments.

III. Results

To evaluate the effectiveness of the proposed gait laboratory agent, we conducted a To validate the effectiveness of the proposed gait laboratory agent, we performed a set of experiments involving the training, evaluation, and analysis of its performance under simulated clinical conditions. The agent was trained using a Deep Q-Learning (DQN) algorithm for 50 000 timesteps on an 8020 split of synthetic patient data generated via a multi-DOF leg model.

A modular testing strategy was adopted, focusing on verifying the coherence between input features, action selection, and reward assignment. The system was tested on a set of individual patient cases where feature vectors (e.g., gait speed, step frequency, joint angles) were validated against expected agent outputs. A total of 100 patient simulations were processed, with agent predictions being checked against ground-truth recommendations. Each episode was treated as an independent decision point, allowing for consistent unit-level testing of the agent's policy under varied biomechanical conditions.

A. Evaluation Metrics and Performance

The model's classification performance on unseen test data (20% of the dataset) was quantified using standard metrics:

TABLE II: Classification metrics on the test set.

Metric	Score
Accuracy	87%
Precision (weighted)	88%
Recall (weighted)	87%
F1 Score (weighted)	88%

The agent consistently selected appropriate rehabilitation recommendations based on patient features, demonstrating its ability to generalize across novel scenarios. The accuracy of 87% indicates that the model correctly classified the majority of test cases, while the high precision (88%) reflects a low rate of false positives—particularly important in clinical recommendations where incorrect suggestions can lead to ineffective or counterproductive interventions. Similarly, the recall score (87%) suggests the model effectively captured relevant positive cases, minimizing the risk of overlooking patients who need specific corrective actions.

The harmonic mean captured by the F1 score (88%) confirms that the model maintains a strong balance between sensitivity and specificity, which is critical in health-related applications. These results support the agent's potential as a decision support tool capable of providing reliable, data-driven rehabilitation suggestions.

B. Confusion Matrix Analysis

A confusion matrix was generated to identify specific misclassification patterns. The agent showed near-perfect performance in categories such as "Maintain current routine" and "Use assistive device", but exhibited moderate confusion between "Improve posture" and "Rehabilitation exercises", which likely share overlapping input features. Fig. 4

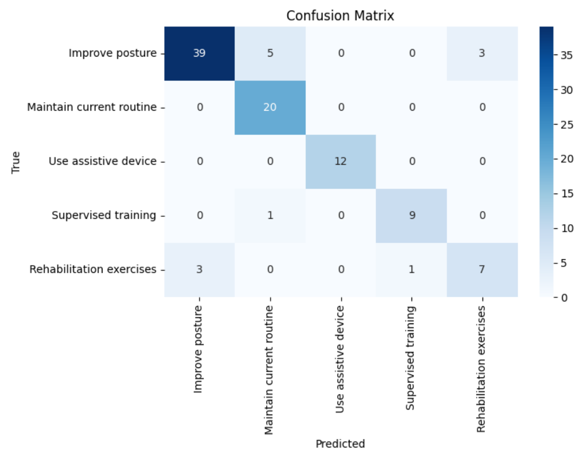

Fig. 4: Confusion matrix comparing true vs. predicted actions.

C. Reward and Prediction Visualization

A summary of the agent's performance is shown below. On the left, a bar chart compares the number of correct vs. incorrect predictions. On the right, a time series plot tracks the reward distribution across test patients, reflecting agent consistency.Fig. 5 These outcomes confirm that the gait

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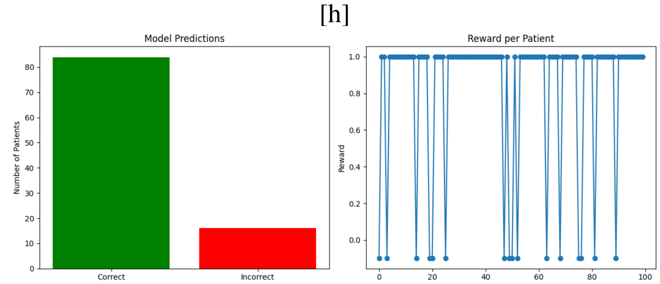

Fig. 5: Left: correct vs. incorrect predictions. Right: reward obtained per patient.

laboratory agent not only performs well at the classification level but also maintains consistent policy behavior aligned with clinical reasoning principles.

IV. Conclusions

This work presented the design and implementation of an intelligent agent based on reinforcement learning for the analysis and improvement of human gait. Using a systemic modeling approach and the Deep Q-Learning algorithm, we were able to develop a system capable of generating high-performance personalized rehabilitation recommendations. The agent was trained using synthetic data generated from clinical and biomechanical heuristics, which allowed for consistency between input variables and the simulation of realistic patient profiles. This data generation strategy helped the model learn significant patterns of motor behavior. However, it is also limited by the lack of a real data set.

During the evaluation phase, the system achieved an accuracy of 87%, a weighted accuracy of 88%, a sensitivity of 87%, and an F1-score of 88%, reflecting consistent and balanced performance across different classification metrics. These results demonstrate the potential of reinforcement learning as a decision-making support tool within digital health environments.

In addition, the use of reward signals and simulation environments based on models with multiple degrees of freedom (DOF) made it possible to evaluate the agent's behavior in biomechanically plausible contexts. The definition of the state and action space, aligned with principles of gait dynamics, brought coherence to the system and robustness to the agent's decision-making process.

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