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Gait Lab Agent
Technical Report

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Glosary

Reinforcement Platforms Measure the forces that the body exerts against the ground during walking. They help identify imbalances, gait patterns, or overload in any limb. Provide data such as moments and force.

Transducers Transform physical signals (such as pressure or vibration) into electrical signals that can be analyzed. They allow for precise measurement of mechanical interactions, useful for detecting anomalies.

Electromyo-graPhy (EMG) Records the electrical activity of muscles as they contract. Detects muscle imbalances, levels of exertion, and coordination between muscles. Provides information about the electrical potentials that reflect muscle activation.

Electrogo-niometers Electronic devices used to measure the angle and range of motion of joints in real-time. They provide continuous data on joint displacement during dynamic activities such as walking, enabling accurate analysis of kinematic patterns and detection of irregular movement or joint limitations.

Optoelectronics Fiber optic technology to carry an input light signal that is modulated according to a measured object magnitude and then collected by a detector, conditioned and processed.

Transmitter The Transmitter is responsible for sending the data collected by the Cinematic Module to both the App and the Storage System. This ensures that the captured motion data is not only preserved but also immediately accessible for visualization and interaction by users.

Insight Engine Is the intelligent module of the Gait Laboratory Agent responsible for analyzing the processed motion data and extracting meaningful insights.

Agent An autonomous system or entity capable of perceiving its environment, processing information, and taking actions to achieve specific goals. In this project, the agent simulates the role of a gait laboratory by analyzing data and providing recommendations.

Pathology A medical condition or disease that affects the structure or function of the body. In gait analysis, pathologies are often associated with irregular walking patterns or impaired motor function.

Cybernetics An interdisciplinary field focused on control systems, communication, and feedback in biological, mechanical, and computational systems. It plays a key role in designing adaptive and self-regulating agents.

Artificial Intelligence (AI) The branch of computer science focused on developing systems that can perform tasks that typically require human intelligence, such as learning, reasoning, decision-making, and pattern recognition.

Systems Science An approach to understanding complex systems by analyzing the interactions between components, feedback loops, and emergent behaviors. It provides the conceptual foundation for modeling the human gait as a dynamic, interconnected system.

Gait The manner or pattern of walking. It involves a complex coordination of muscles, joints, and neural signals, and is often used as a diagnostic tool for assessing motor function.

Insight Engine A system designed to extract, analyze, and interpret data to generate meaningful insights. In this context, it refers to the intelligent component of the agent that delivers personalized recommendations based on gait data.

Feedback Loop A process in which part of a system's output is returned as input, helping the system adjust and regulate its behavior. Positive and negative feedback loops are key to understanding gait stability and adaptation.

Nonlinear Dynamics A mathematical framework used to describe systems in which output is not directly proportional to input. This is relevant for modeling human movement, which is inherently complex and variable.

Simulation The imitation of a real-world process or system over time, often through computational models. Used in this project to test the agent's behavior under various conditions without needing physical trials.

Reinforcement Learning A type of machine learning where an agent learns optimal behavior through rewards and penalties. It is used to train the agent to improve its recommendations over time based on feedback.

C3D File Format A standard file format (.c3d) used to store biomechanical data such as motion capture, force plate, and EMG signals. It is widely used in gait analysis and movement science.

Kinematics The branch of mechanics that deals with motion without considering the forces causing it. In gait analysis, it involves studying joint angles, segment trajectories, and velocities.

Kinetics The study of forces and torques that cause motion. It complements kinematic data to fully understand movement patterns.

Noise Unwanted variations or disturbances in data, often due to sensor inaccuracies or unpredictable variables. Noise reduction techniques are important for improving the precision of gait analysis.

Specialist A human expert in gait analysis or rehabilitation who can validate the agent's recommendations and guide the learning process by providing reward signals or feedback.

Clinical History A detailed and confidential medical record that includes relevant information about a patient's health status. It contains medical background, previous diagnoses, treatments, physical examinations, and clinical evolution. In this project, it is used to contextualize patient data and adjust the agent's analysis accordingly.

Nonlinear Factors Variables or elements whose relationship with the system does not follow a direct proportionality. In gait analysis, nonlinear factors reflect the complexity of human behavior, where small variations may lead to large effects in movement. Studying these factors is essential to understand natural variability and detect potential anomalies.

Intelligent Agent A decision-making system capable of perceiving its environment and taking actions based on a trained model. In this project, it suggests rehabilitation recommendations based on patient data.

Reinforcement Learning A machine learning paradigm where an agent learns optimal behavior through interactions with an environment, receiving rewards or penalties for its actions.

DQN (Deep Q-Network) A reinforcement learning algorithm that uses deep neural networks to approximate Q-values and make decisions in environments with discrete action spaces.

Custom Gym Environment A simulation environment built using the Gymnasium library, tailored to represent patient states and allow interaction with the agent for learning and evaluation.

Multi-DOF Model A biomechanical model representing a human leg with multiple degrees of freedom (DOF), such as hip, knee, and ankle, used to simulate gait patterns in patients.

Data Preprocessing A set of techniques applied to raw patient data to prepare it for machine learning. This includes normalization, encoding of categorical variables, and handling missing values.

Recommendation A proposed rehabilitation or gait improvement strategy suggested by the agent (e.g., "Increase cadence" or "Improve posture"), based on the patient's condition.

Patient Simulation The artificial generation of patient data using mathematical or biomechanical models, allowing the training and evaluation of the agent without real patient datasets.

Agent Evaluation The process of assessing the model's performance using a test dataset and reporting metrics such as accuracy, precision, recall, and F1-score.

Confusion Matrix A table used to visualize the performance of a classification model by showing the comparison between actual and predicted recommendations.

Heuristic Rules Expert-based or logical rules used to validate the agent's recommendations and assess their plausibility against predefined knowledge.

Feedback Loop A dynamic cycle in which the agent's decisions affect the environment, and the resulting changes are used to improve future decisions through learning.

Abstract

This report presents the research, methodologies used, and results obtained for the development of the GaitLab project, whose objective is to develop an artificial agent capable of objectively and automatically analyzing human gait. The agent system is composed of fundamental elements such as dynamic and kinematic variables related to locomotion. These are taken into account to generate personalized diagnoses along with recommendations to improve gait quality. For the implementation of the GaitLab agent, fundamental concepts from systems science were applied, such as systems theory, cybernetics, and artificial intelligence (AI). In addition, computational simulations of the agent's environment were constructed, and machine learning algorithms such as DQN and reward signals were implemented. A dataset on patient gait and a multi-DOF leg model were also used to enable a modular understanding of gait. Finally, it is concluded that a systemic thinking approach is essential to understanding the internal dynamics of the system, and that reward signals provided by a specialist are crucial to guiding the agent's learning process.

Chapter 1

Introduction

Human gait is one of the most essential motor functions of human beings, and its study represents a key area in injury prevention, physical rehabilitation and performance improvement. Although it is an everyday activity, the way we walk can be indicative of biomechanical or neuromuscular alterations that affect quality of life. Traditionally, gait analysis has been performed in specialized laboratories using advanced motion capture systems and physiological signal analysis. However, these laboratories can be expensive and limited in availability, reducing their scope for individuals requiring frequent or real-time monitoring.

Given this need, we propose the design of an artificial agent capable of simulating the functioning of a gait laboratory. This agent seeks to analyze the dynamic and kinematic patterns of human movement through data obtained from sensors or simulations, using principles of systems thinking, cybernetics, artificial intelligence, and chaos theory. Its objective is to collect a series of relevant data on patients' gait. It then provides a gait analysis using this data, making the process more accessible, continuous, and adaptive, with personalized feedback for both rehabilitation patients and healthcare professionals.

This report details the conceptual design, theoretical basis, and tools considered for the implementation of this agent. These highlight the use of environmental simulations to obtain data and evaluate the model.

Chapter 2

Literature Review

For the development of the project we used information related to gait, learning algorithms and mathematical concepts. With which we defined and contextualized the designs, descriptions and documentation. The concepts and articles we used were the following.

- **Development of a Gait Laboratory with Synchronic Integration Through a Modular Architecture by** Martínez Carrillo et al. (2010):
  The article presents the development of a gait laboratory with a modular architecture that allows for the synchronous acquisition of multiple types of biomedical signals relevant to the analysis of human gait. The system was designed with a clinical and rehabilitation focus, seeking to provide an objective assessment of patients with locomotor disorders such as cerebral palsy, stroke, or orthopedic disorders.
  The laboratory was designed with an architecture of independent modules, which provides flexibility, easier maintenance, and the possibility of updating or replacing components without affecting the entire system. Each module performs a specific function in gait analysis:

  - **Kinetics:** It uses optical capture systems and sensors to measure displacements, joint angles, and trajectories. This module allows movement to be described in a quantitative and reproducible manner.
  - **Dynamics:** It uses force platforms that record ground reaction forces during walking. It is used to calculate joint moments and evaluate body weight distribution.
  - **Electromyography (EMG):** Records superficial muscle activity. This module is essential for analyzing the sequence and timing of activation of specific muscles during each phase of the gait cycle.
  - **Energy consumption:** Estimate the physiological cost of movement using indicators such as oxygen consumption or heart rate.

  Uno de los mayores aportes del sistema es la sincronización temporal entre los módulos, lograda mediante un software central de integración. Esto permite que las señales cinemáticas, dinámicas y eléctricas se alineen en el tiempo para un análisis correlacionado más preciso. Así, por ejemplo, se puede asociar la activación de un músculo con una fase específica de la marcha y con la magnitud de fuerza ejercida en ese momento.

  The system includes graphical visualization and data processing tools, which facilitate clinical interpretation by therapists, engineers, and physicians. Similarly, the modular architecture also allows for scalability and adaptability, as new sensors or systems can

be integrated without the need to completely redesign the platform.
Thanks to the study and implementation proposed by Martínez Carrillo et al. (2010), It was possible to identify and understand fundamental elements for the design of our gait laboratory agent system. The modular structure, the synchronization of multiple sources of kinematic, dynamic, electromyographic, and energy data, and the clinical application in real contexts provided us with a solid basis for defining the technical and functional components that our system must integrate. Furthermore, it allowed us to understand more clearly how the laboratory should operate in terms of data acquisition, processing, and analysis, thus guiding the development of an agent capable of issuing objective and personalized recommendations to improve users' gait.

- **Human walking phases by** Martín Nogueras et al. (1998):
  In this article Martín Nogueras et al. (1998), they present a detailed description of the normal gait cycle, dividing it into functional phases that allow for a structured analysis of the biomechanical events involved in each moment of movement. Their proposal focuses on clinical practice, especially in physical therapy and rehabilitation, and constitutes a key reference for understanding the normal phases of the human gait pattern.
  The gait cycle is defined as the sequence that begins with the heel of one foot making contact with the ground until that same foot makes contact again. It consists of periods of support and swing, and is divided into four main functional phases:

  - **Boost Phase:** This is the moment when both feet are in contact with the ground, but the body's weight is transferred to the opposite leg, while the back foot begins to lift off to initiate forward momentum. In this phase, the following biomechanical events can be considered: active extension of the hip and knee, as well as plantar flexion of the ankle, which generates the propulsive force. The following muscles are involved: the triceps surae, gluteus maximus, and hamstrings stabilize the hip.
  - **Heel Strike Phase:** This is the initial phase of the cycle, when the heel of the leading foot makes first contact with the ground. The following biomechanical events can be considered in this phase: knee flexion to absorb impact, controlled pelvic anteversion, and dorsal flexion of the ankle during landing. The following muscles are involved: the tibialis anterior controls eccentric plantar flexion, the quadriceps absorb the impact through eccentric contraction, and the gluteus medius stabilizes the pelvis in the frontal plane.
  - **Medium Single-Leg Support Phase:** This occurs when the body is completely supported by one leg. It is a critical phase for stability and postural control. In this phase, the following biomechanical events can be considered: the hip on the opposite side descends slightly and is counteracted by the contraction of the gluteus medius on the supporting side, the center of mass passes over the supporting foot, and the knee is almost fully extended with the ankle in a neutral position. The following muscles are involved: the gluteus medius and minimus: lateral stabilization; soleus and gastrocnemius: control the forward movement of the body; and the spinal erectors: stabilize the trunk.
  - **Oscillation Phase:** This is the phase in which the foot is in the air, moving forward to prepare for the next step. It involves the following muscles: iliopsoas: hip flexion; hamstrings: slow down the leg before contact; and tibialis anterior: keeps the foot in dorsiflexion to prevent dragging.

  The article by Martín Nogueras et al. (1998) was fundamental to gaining an in-depth

understanding of the normal gait pattern from a functional and clinical perspective. His approach, based on a detailed description of the different phases of the gait cycle, allowed us to construct a structured view of how proper gait should develop, which is essential for detecting deviations and defining objective analysis criteria within our gait laboratory agent system.
Through the functional division into push-off, heel strike, single-leg support, and swing phases, clear guidelines are established on when and how the main joints and muscle groups should be activated, and what types of movements are expected at each moment of the cycle. This segmentation not only provides a robust theoretical framework, but also enables the practical translation of gait into measurable and comparable terms.
This model provided us with a clear perspective on which biomechanical and temporal variables should be observed in a patient's gait analysis.
The clarity with which the article defines the transitions and functional requirements of each phase also helped establish thresholds and benchmarks so that the analysis agent can identify when a phase is executed correctly or presents clinical deviations. In this sense, this resource not only instructed us on physiological gait, but also provided us with the basis for operationalizing that gait in terms of observable, interpretable, and comparable data, which is key in automated systems geared toward rehabilitation and optimization.

- **Learning with Deep Q Learning by** Hernandez (2018):
The article by Hernandez (2018) provides a clear and progressive introduction to the field of deep reinforcement learning, with a particular focus on the evolution of the traditional Q-Learning algorithm towards Deep Q-Learning (DQL). This transformation is highly relevant to the design and implementation of an intelligent agent such as the one proposed in our gait laboratory, as it guides us on how a system can learn to make complex decisions based on previous experiences in dynamic and multidimensional environments such as the human gait pattern.
Initially, the article reviews the functioning of traditional Q-Learning, in which an agent learns an optimal action policy by iterating Q values associated with state-action pairs. This method, although effective in simple environments, has serious limitations when faced with large or continuous state spaces, as is the case in biomechanical applications. Q tables become inefficient and unable to generalize.
To overcome these limitations, the article explains how DQL introduces deep neural networks as function approximators $Q(s, a)$, this allows the agent to generalize its behavior even in situations it hasn't directly explored. This approach is especially useful in environments where there are a lot of possible combinations of inputs (like joint angles, support times, and gait phases).

Similarly, let us understand what deep reinforcement learning is. This learning consists of algorithms based on function approximation, i.e., there is a function that approximates the Q-values of actions. Instead of maintaining a table of Q values, we use functions as neural networks to predict the Q values of the actions in a specific state. This algorithm consists of the following steps: The agent observes the current state of the environment. If a random number is less than or equal to epsilon, the agent will take a random action; otherwise, DQN predicts the Q values and the action with the maximum Q value. The next state, Reward, and a terminal variable are stored inside the replay memory.After a while, when there are enough examples in memory, the agent trains DQN by sampling a batch of experiences. The set of current states is considered a feature and the label represents the target values computed as. The target network is periodically updated with the main network.

Implementing DQL to build the walking laboratory agent may be a good option. This is because it can handle complex environments such as human walking.

- **Theoretical and Computational Analysis of Normal and Pathological Gait: a Review** by Cifuentes et al. (2010):
  The article by Cifuentes et al. (2010) provides an in-depth look at how biomechanical, statistical, and neuromuscular models can be used to describe and differentiate between healthy and pathological human gait. This systematic review is a valuable guide for selecting relevant variables and analysis methodologies in the gait laboratory.
  The authors emphasize that walking results from the interaction between the neuromuscular, musculotendinous, and osteoarticular systems. This interconnected approach is fundamental to understanding not only normal movement, but also possible clinical deviations.
  The **static models** are based on the quantitative analysis of variables measured from a population, in order to establish averages, standard deviations, and other metrics that serve as a reference for comparing an individual pattern. These types of models are simple to implement and allow for the detection of obvious deviations from a "normal" pattern. They are also useful in epidemiological and screening studies.
  On the other hand, the **mechanical models** which represent the human body as a set of segments connected by joints, with defined physical properties (mass, inertia, length, etc.). Within this category, the following stand out:

  - **Inverted pendulum models:** They consider the leg to be a pendulum that swings around a fixed point (the hip).
  - **Multi-segment models:** They represent the body in multiple degrees of freedom, allowing for more detailed analysis of intersegmental movement and complex kinematics.

  These types of models allow forces, moments, and power to be estimated at each joint. Similarly, they provide information about the dynamics of the musculoskeletal system.

  Finally, we have the **Musculoskeletal and neuromuscular models** combine the mechanical dynamics of the body with representations of muscle function and neurological control. They are the most complex and realistic, and allow us to understand how and why a particular movement occurs. These types of models provide information about the functional origin of gait disorders. They are also particularly useful for designing personalized interventions and rehabilitation programs.
  The article highlights that no single model is sufficient to capture the complexity of human gait. Therefore, a hybrid approach is proposed, where statistical models are used for quick references, mechanical models for dynamic analysis, and neuromuscular models for a deep and functional understanding.
  This approach has been key to defining the architecture of the proposed gait laboratory agent, combining classic biomechanical analysis with intelligent modules that interpret movement patterns and suggest corrections based on reinforcement learning.

- **Dynamic Modeling Method of Multibody System of 6-DOF Robot Based on Screw Theory** by Cheng et al. (2022):
  The article by Cheng et al. (2022), it represents a significant advance in the dynamic modeling of complex robotic systems, particularly those with multiple degrees of freedom (multi-DOF). His proposal integrates screw theory with a robust mathematical formulation based on quaternions, all geared toward highly complex multibody systems, such as a 6-DOF robot. This approach is highly relevant to fields such as biomechanics, rehabilitation, and medical robotics, where human joint movements can also be modeled as multibody systems with multiple degrees of freedom.
  A multi-DOF (multiple degrees of freedom) system is one in which each joint or component can move in several independent directions or axes. In the human body, for example: the hip can move in flexion/extension, abduction/adduction, and internal/external rotation 3 DOF, or the knee, although it mainly performs flexion-extension, also has a certain degree of axial rotation 1 to 2 DOF.
  Cheng et al. (2022), they apply this theory to represent the spatial relationships between connected rigid bodies, reducing algebraic complexity and increasing modeling accuracy. Instead of treating translational and rotational movements separately, screws integrate them into a single mathematical entity.
  Although the article focuses on industrial robotic arms, its concepts are highly transferable to an intelligent gait analysis agent. Given that the human lower limb can also be viewed as a multibody system with multiple degrees of freedom, the need to accurately represent its movements is fundamental. The use of compact and decoupled models allows the agent to process kinematic and dynamic data in a modular and real-time manner, enabling near-instantaneous clinical recommendations. The modularity and scalability of the model are consistent with the proposed structure for the gait agent, where each module (capture, analysis, recommendation) can draw on accurate dynamic descriptions.

Chapter 3

Background

Human gait analysis is a fundamental tool in physical therapy, rehabilitation, orthopedics, and biomechanics. It allows for the detection of functional alterations, the quantification of treatment progress, and the design of personalized interventions, with the aim of improving and preventing impairments in human gait. The construction of the GaitLab agent and the improvement of this analysis require a combination of interdisciplinary knowledge ranging from biomechanics to artificial intelligence.

- **Normal human walking:** It is structured into two main phases: the support phase (60% of the cycle) and the swing phase (40%), subdivided into key events such as initial contact, mid-support, heel lift, and terminal swing. These phases allow for the analysis of weight distribution, stability, symmetry, and coordination between limbs. Martín Nogueras et al. (1998). Understanding this structure is essential for defining which variables should be monitored, such as contact time, joint angles, linear velocities, and center of mass trajectories.

- **Gait analysis models:** There are three main approaches to modeling and analyzing gait. Cifuentes et al. (2010): statistical models, mechanical models, and neuromuscular models

- **Multi-DOF system dynamics:** lThe lower limb can be represented as a multibody system with multiple degrees of freedom (multi-DOF), similar to a 6-axis robot. Cheng et al. (2022) they propose an efficient and scalable model based on screw theory and quaternions to describe these systems, enabling accurate and stable simulations even with complex three-dimensional movements.
  This type of modeling is key to interpreting the movement data captured by sensors and understanding the dynamic causes of gait disturbances.

- **DQL:** To adapt the analysis to different users and conditions, Deep Q-Learning (DQL) is incorporated, a deep reinforcement learning technique that allows an agent to learn to make optimal decisions through interaction with an environment. This technique is useful for modeling clinical decisions, such as suggesting adjustments to gait based on the patient's current condition.
  DQL combines deep neural networks with reinforcement algorithms, enabling generalization, noisy data handling, and continuous feedback, which is ideal for personalized and intelligent systems.

- **Metrics for evaluating the agent:** To validate the effectiveness of the laboratory walking agent in the recommendation task, classic model evaluation metrics are used, such as:

- **Accuracy:** proportion of correct predictions out of the total number of cases. It is useful as a general metric, although it can be misleading in unbalanced datasets.
- **Precision:** it measures how many of the positive recommendations or classifications were actually correct. This is important when you want to minimize false positives.
- **Recall:** evaluates the system's ability to detect all true positive cases, such as correctly identifying all gait abnormalities present.
- **F1 Score:** it is the harmonic mean between precision and recall. It is especially useful in clinical settings where both false positives and false negatives must be minimized in a balanced manner.

Given this scenario, the development of intelligent systems that allow modeling gait from a systemic and cybernetic perspective, integrating dynamic simulations and learning algorithms to interpret the data in an objective and quantitative manner is warranted. The possibility of implementing artificial agents with feedback and adaptation capabilities opens new opportunities for the personalization of diagnosis and intervention, contributing significantly to rehabilitation, injury prevention and optimization of physical performance in various clinical and sports contexts.

Chapter 4

Objective

4.1 General Objective

The purpose of this project is to develop an artificial agent of a gait laboratory, with the ability to analyze data and be able to generate recommendations to patients. Making use of fundamental concepts of systems theory, cybernetics and AI. In order for patients to optimize their gait patterns.

4.2 Specific objectives

- Develop an evaluation strategy that represents patient gait through simulated features such as Gait Speed, Step Frequency, Knee Angle, and Pelvic Deviation, using a multi-DOF leg model. This enables the agent to interpret gait patterns and generate personalized recommendations, without relying on raw motion capture signals.
- Design and implement a modular architecture for data capture and analysis in the gait laboratory that allows the integration of devices from different manufacturers, following standards such as CSV for the synchronous management of dynamic, kinematic and physiological variables.
- Evaluate the accuracy and usefulness of the adaptive agent through feedback, simulations and clinical cases, comparing its performance against traditional methods of observational or quantitative analysis.
- Apply the Deep Q-Learning (DQN) algorithm to train an agent that learns to identify optimal intervention or assessment times based on the patient's biomechanical state and a clinically relevant reward function.

Chapter 5

Scope

This project focuses on the design and development of a gait laboratory agent capable of analyzing human gait data and generating personalized recommendations for improvement. The main focus is on simulating an environment with multi-DOF model concepts, training the agent with synthetic data, testing the agent with simulation data, and evaluating the recommendations generated. **The study includes:**

- The development of causal diagrams and simulation models representing information flows, influencing factors, nonlinear relationships and feedback loops.
- The construction of a computational model using tools such as Gymnasium to simulate the agent's behavior in different scenarios.
- The design of a basic functional software that emulates some key functions of the intelligent walking laboratory.
- The exploration of the role of the specialist and the patient within the system as actors contributing to the adaptive dynamics of the agent.
- Generating synthetic data on human gait for model training.
- The use of metrics such as precision, recall, accuracy, and F1 score to evaluate system performance.
- The development and integration of a decision-making model based on deep reinforcement learning.

The study excludes:

- The physical implementation of the lab or the use of real sensors to capture gait data.
- Clinical validation with real patients or certified therapeutic interventions.

With this scope, it is intended to deliver a solid conceptual and functional basis that allows not only to understand the system from a dynamic perspective, but also to move towards an initial prototype that will serve as a starting point for future real implementations.

Chapter 6

Assumptions and Limitations

It is essential to identify the assumptions on which the project is built, since these represent conditions or factors that are not known with certainty, but are considered valid within the development context. Recognizing these assumptions allows the scope of the proposed system to be more precisely defined and clear boundaries for the behavior of the artificial agent to be established.

6.1 Assumptions

In the development of the artificial agent for gait analysis, certain necessary conditions have been assumed to facilitate the design and guide the scopes of the system. These assumptions do not necessarily represent proven or ideal situations, but are considered reasonable within the context of the project. These are:

- It is assumed that synthetic data used in this study encompassing kinematic, dynamic, and electromyographic information are sufficiently accurate and representative of actual patient behavior. These datasets serve as the primary input for training and evaluating the agent's algorithms.
- It is assumed that the environment in which these data are collected is controlled or has stable conditions, thus minimizing external disturbances.
- It is assumed that a clinically validated dataset will be available to train and validate the agent's analysis models. However, at this development stage, this dataset may be built from simulated data, publicly available databases, or documented case studies.
- The system assumes that a domain expert (e.g., clinician, physiotherapist, biomechanist) is involved in the loop to interpret the agent's output, fine-tune parameters, and provide feedback. This expert involvement is particularly critical during the training and calibration phases, where the definition of reward functions and behavioral rules can significantly affect agent performance.
- It is assumed that the human body can be represented using simplified multi-DOF biomechanical models (e.g., linked rigid segments and ideal joints), which capture the essential characteristics of gait without modeling soft tissue dynamics or complex joint behavior.
- It is assumed that while the agent may produce accurate recommendations, the internal decision-making process of the model (e.g., neural networks) may not always be directly interpretable by humans.

6.2 Limitations

Despite the potential of the proposed laboratory agent, the development of the project faces several limitations:

- First, the availability of real data is limited; most tests and analyses are based on simulations and theoretical models, which may differ from clinical or field scenarios.
- The lack of access to specialized devices, such as high-precision motion capture sensors or force platforms, limits the accuracy of the input data.
- Is that validation of the system with real users has not yet been carried out, which prevents concrete evaluation of the agent's effectiveness in a real rehabilitation or clinical analysis setting.
- The machine learning and feedback model still relies on idealized assumptions, such as that the specialist's recommendations are always accurate and that patient behavior is predictable.
- The timing and scope of the academic project condition the depth of implementation. Many functionalities are designed for a more robust future version, so the current results should be interpreted as an initial stage of development and conceptual validation.
- Due to the use of deep learning (e.g., Deep Q-Learning), some of the recommendations made by the agent may not be easily interpretable by clinicians. This could hinder trust or clinical adoption, especially in sensitive rehabilitation contexts.

Chapter 7

Methodology

The methodologies used for the development of this project are grounded in systems theory, artificial intelligence, and cybernetics. From systems science, systemic thinking was applied to model the agent's behavior, supported by the design of system and causal diagrams. To enable autonomous learning, a Deep Q-Learning (DQN) algorithm was implemented and trained using a custom Gymnasium environment (GaitEnv) tailored to gait analysis.

Patient data was incorporated through a combination of real clinical records and simulated observations generated with a multi-DOF leg model, providing biomechanical signals such as joint angles and gait speed. This allowed the agent to receive diverse and realistic inputs.

Training and evaluation of the agent were conducted using the Stable-Baselines3 library, and key performance metrics such as accuracy, precision, recall, and F1 score were computed to assess its behavior. The simulation of dynamic environments and patient responses was achieved using Gymnasium, and feedback was incorporated through a reward function based on correct or incorrect recommendations. The system was continuously evaluated and visualized through graphs, including confusion matrices and reward trends, closing the loop with cybernetic feedback principles.

7.1 System Dynamic Analysis & Design

A systems science, artificial intelligence and cybernetics approach was used to design the walking lab agent in order to understand and model the complexity of the system. El sistema propuesto para el Agente de Laboratorio de Marcha se conceptualiza como un entorno dinámico e inteligente, capaz de adquirir, procesar y analizar datos biomecánicos en tiempo real. Su arquitectura se compone de múltiples módulos interconectados que permiten una evaluación integral del patrón de marcha y la generación de recomendaciones personalizadas. El diseño sigue un enfoque modular y retroalimentado, el cual se detalla a continuación(Figure 7.1).

- **Systems inputs:**
  - **Patient medical history:** Información médica previa relevante para contextualizar el análisis.
  - **Training data:** Previously stored or simulated data that enables model learning and calibration.

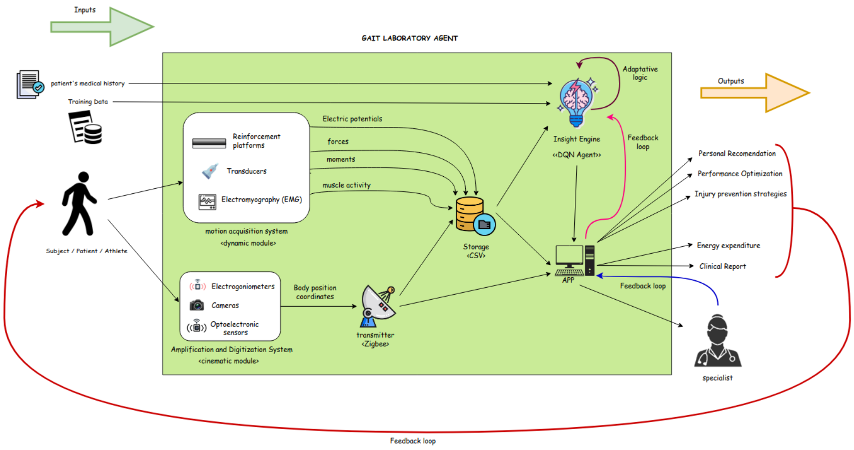

Figure 7.1: Gait Laboratory System Diagram

  - **Subject under evaluation:** Patient, athlete, or system user whose kinematic and dynamic signals are captured for analysis.

- **Dynamic Module:** This module is responsible for capturing physiological and mechanical information:
  - **Reinforcement platforms:** Captures forces and moments exerted during walking.
  - **Transductores:** They transform physical signals into usable digital data.
  - **Electromyography (EMG):** Measures electrical muscle activity.

- **Kinematics Module:** It uses sensors to record three-dimensional body movement:
  - **Electricalgoniometers:** They measure joint angles.
  - **Cameras and optoelectronic sensors:** Captures spatial coordinates of the body in motion.

- **Transmisor ZigBee:** Enables wireless data communication to the central system.

- **Storage System:** All acquired data is stored in CSV format, allowing for subsequent structured and synchronized analysis. This system acts as a temporary and permanent database for training and analysis.

- **Insight Engine:** This core component incorporates a deep reinforcement learning model (Deep Q-Learning) that enables adaptive interpretation and the generation of personalized recommendations.

- **Systems outputs:** It consists of personalized recommendations, performance optimization, injury prevention strategies, and energy expenditure estimates.

- **Feedback Loop:** There are three feedback cycles within the system. Two of them occur within the system itself in order to improve the results predicted by the model. The third cycle consists of messages for the subject, which are simple recommendations that seek to shed light on the condition of the system.

The stock-and-flow model (Figure 7.2) presented allows us to visualize the dynamic relationships between the different components of the gait assessment system, from initial preparation to the generation of personalized recommendations. This approach allows us to identify

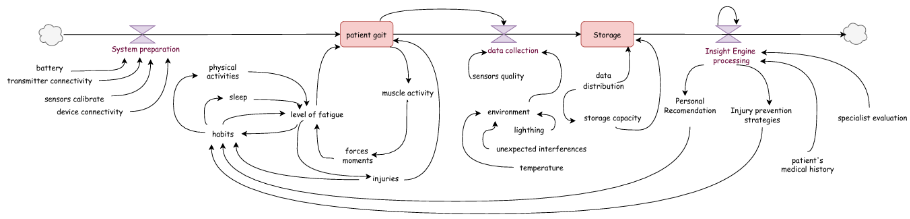

Figure 7.2: Causal Diagram for Gait Lab

latent variables, nonlinearities, feedbacks, and external conditions that affect the performance of the system. Some of its important parts are:

System preparation is a critical phase in ensuring that future measurements are valid. It includes: sensor calibration, device and transmitter connectivity, and battery status. These variables ensure that the sensors can operate continuously and reliably. Any failure at this initial stage will affect data collection and, therefore, the accuracy of the analysis.

On the other hand, the patient's gait is the central component of the system, influenced by multiple internal and external factors: level of physical activity, sleep habits, accumulated fatigue, general habits (nutrition, sedentary lifestyle, etc.), and the presence of previous injuries or discomfort. Gait is also modulated by muscle activity and the forces and moments generated during locomotion. This block interacts with almost all elements of the system, and any variation in these conditions modifies the data generated.

Once the system is ready and the gait is executed, the sensors collect kinematic and dynamic information from the patient. This stage is conditioned by the quality of the sensors, the physical environment (lighting, temperature, noise), and possible unexpected interference. These conditions can amplify or distort the signals, which directly affects the fidelity of the model. Therefore, it is a block that is sensitive to exogenous factors, and its cascading effects can influence subsequent processing.

The collected data is sent to a storage unit where it is organized, labeled, and stored for later analysis. Here, two key factors determine its effectiveness: the capacity of the storage system (which limits the amount of historical data available) and data distribution (which affects accessibility and query speed). In addition, this block is responsible for maintaining clinical traceability, allowing longitudinal comparisons of patient progress.

Este componente actúa como el núcleo de razonamiento del sistema. Utiliza modelos de aprendizaje automático o lógica adaptativa para interpretar los datos almacenados, compararlos con el historial médico del paciente y generar recomendaciones personalizadas. Este módulo también integra estrategias de prevención de lesiones y optimización del rendimiento físico. Su eficacia está directamente relacionada con la calidad del entrenamiento previo, la granularidad de los datos y la supervisión clínica recibida.

7.2 Inverted Pendulum Model

Human gait describes a set of movements of different parts of the human body that enable people to move around. This set includes the alternating and rhythmic movements of the lower limbs and trunk, which, when coordinated, form the human locomotor system. Normally, doctors, specialists, and, in this case, our agent focus on analyzing gait patterns in order to determine recommendations for optimization. In relation to this, gait pattern analysis is performed by studying the structural relationships of gait. One of these relationships is the cyclical movement in human trajectory, which is represented by the inverted pendulum. Cifuentes et al. (2010).

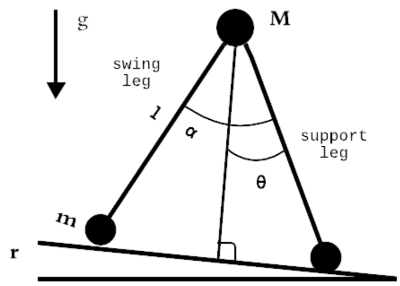

Figure 7.3: Double Inverted Pendulum Module

The model in Figure 4 was proposed by Garcia and Coleman. Garcia et al. (1998), who extend the concept of an inverted pendulum model in order to approximate the observed movement of walking. This model represents the relationship between body mass (M), foot mass (m), the supporting leg, the swinging leg, and the measurements that influence gravity (g), leg length (l), the angle between the supporting and swinging legs (α), and the slope of the inclined plane (r). With this, the angle at which a step is taken can be determined.

$$\alpha = \frac{g}{l} * cos(\alpha) \tag{7.1}$$

This model can be used to represent the mechanical behavior of the body during walking and its phases, see Figure 5.

7.3 Management & Data Processing

For the management and processing of information within the gait laboratory system, we organized the data into structured components that enable efficient learning and decision-making by the agent. Rather than relying on raw C3D data, we used preprocessed datasets in CSV format that include both physical and clinical information extracted or simulated from gait parameters.

These datasets were generated using artificial intelligence tools, guided by prompts designed to ensure logical consistency and clinical plausibility among variables. This approach ensured that the data was not randomly distributed or contradictory, but instead followed patterns commonly observed in real-world patient populations. Such structure was essential for the agent to identify coherent relationships and learn meaningful recommendations, avoiding overfitting or confusion due to uncorrelated input features.

To facilitate learning and recommendations, the system processes each patient as a feature vector composed of:

- **Numerical Features**: Biomechanical and physiological variables such as age, height, weight, gait speed, knee angle, pelvic deviation, force, moment, EMG signals, and electrical potential.
- **Categorical Features**: Clinical and contextual factors such as previous injuries, fatigue level, and general medical history.
- **Label (Target Variable)**: The expert recommendation provided for the patient, such as *"Improve posture"* or *"Enhance muscle strength"*.

These data are normalized and encoded using a *ColumnTransformer* that applies Min-Max scaling to numerical features and one-hot encoding to categorical features. This preprocessing ensures compatibility with the neural network input requirements of the Deep Q-Learning agent.

The following tables summarize the feature structures:

Table 7.1: Numerical Features

Numerical Features			
Age	Height	Weight	Gait Speed
Force	Moment	EMG	Electrical Potential
Step Frequency	Knee Angle	Pelvic heightDeviation	Energy Expenditure

Table 7.2: Categorical Features

Categorical Features		
PreInjuries	MedicalHistory	FatigueLevel

In addition, the system maintains an implicit experience buffer during training, which stores past patient data, agent actions, and obtained rewards. This allows the agent to learn over time by refining its policy based on previous outcomes.

To support autonomous learning and decision-making in complex state spaces, the system implements the **Deep Q-Learning (DQN)** algorithm. Unlike traditional Q-learning that uses explicit tables, DQN employs a deep neural network to approximate the Q-function:

$$Q(s, a) \approx \text{Neural Network}(s)$$

Through interaction with the environment, the agent learns to:

- Recognize and interpret gait patterns from the input features.
- Predict personalized recommendations for gait improvement.
- Optimize its actions to maximize long-term rewards based on accuracy and consistency of suggestions.

The integration of patient features, reward-driven feedback, and adaptive decision-making empowers the agent to act as a dynamic support system in clinical gait analysis.

7.4 Simulation and Training Environment

The simulation environment was built using **Gymnasium**, allowing the definition of a custom reinforcement learning environment (GaitEnv) tailored to biomechanical gait data. This environment integrates both patient-specific clinical information and biomechanical data generated through a Multi-DOF leg model, simulating realistic motion patterns. The dataset was split into training and testing subsets (80/20).

To replicate patients, a biomechanical model was implemented that captures the dynamics of hip, knee, and ankle joints. These simulations produce signals such as joint angles, velocities, and accelerations, forming part of the agent's observation space. This setup allows the agent to receive realistic gait signals influenced by clinical variables such as age, fatigue level, or injury history.

State and Action Spaces

The state space includes normalized clinical and biomechanical variables such as:

- Age, Height, Weight.
- Energy expenditure, Muscle force, Electrical potential (EMG).
- Gait speed, Step frequency.
- Joint angles (knee, pelvis), Fatigue level.

The action space consists of discrete recommendations:

- Improve posture.
- Increase cadence.
- Enhance muscle strength.
- Adjust foot strike.

Reward System

The agent receives a positive reward when its predicted recommendation matches the correct label associated with each patient. Incorrect predictions are penalized with a small negative reward. This structure encourages learning that optimizes accuracy over time.

Table 7.3: Reward Structure for Gait Agent

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

A batch of synthetic patients is generated using the DOF model and saved in CSV format. These records are then used to test the generalization of the trained agent beyond real data, ensuring it can handle novel but realistic gait patterns.

The agent receives a positive reward when the selected action (recommendation) matches the ground truth label (correct intervention). A small negative reward is given when the agent makes an incorrect recommendation. This encourages exploration and learning without severely penalizing mistakes.When the recommendation field is not available (e.g., during simulation), no reward is assigned, but the agent continues interacting with the environment.

Environment Design

To train and evaluate the gait laboratory agent, we designed a custom simulation environment based on the `gymnasium` interface. This environment, `GaitEnv`, models the patient's state, the agent's decision process, and the feedback loop through a reward system.

A key innovation in the environment is the integration of a biomechanical leg model with multiple degrees of freedom (DOF), which simulates gait dynamics. The model simulates angular positions and velocities at the hip, knee, and ankle joints, allowing more realistic representation of patient variability.

```
class MultiDOFLeg:
    def __init__(self, dt=0.02):
        self.dt = dt
        self.reset()

    def reset(self):
        self.state = np.array([
            np.random.uniform(-0.2, 0.2), 0.0,
            np.random.uniform(-0.1, 0.1), 0.0,
            np.random.uniform(-0.1, 0.1), 0.0
        ], dtype=np.float32)
        return self.state

    def step(self, torques):
        hip_torque, knee_torque, ankle_torque = torques
        # Update state using basic physics (acceleration integration)
        ...
        return self.state
```

Listing 7.1: MultiDOFLeg simulation model

The output of this model (a 6-dimensional vector) is concatenated with the patient feature vector to form the complete observation. This increases the diversity of states the agent is exposed to and makes learning more robust.

Observation and Action Spaces

The environment combines structured patient data with leg dynamics to form the observation. The action space is discrete and consists of a set of predefined rehabilitation recommendations:

```
self.actions_list = [
    "Improve posture",
    "Increase cadence",
    "Enhance muscle strength",
    "Adjust foot strike"
]
self.action_space = spaces.Discrete(len(self.actions_list))
```

Reset and Step Logic

Each call to `reset()` samples a random patient and resets the leg model. The `step()` function receives an action (recommendation index), simulates the leg model if enabled, computes the reward, and transitions to the next patient.

```
def reset(self):
    ...
    obs_patient = self.processed_features[self.current_index]
    obs_leg = self.leg_model.reset()
    return np.concatenate([obs_patient, obs_leg]), {}

def step(self, action):
    ...
    torque_vector = np.array([action - 1]*3, dtype=np.float32)
    obs_leg = self.leg_model.step(torque_vector)
    obs = np.concatenate([obs_patient, obs_leg])
    reward = 1.0 if action == correct_action else -0.1
    ...
    return obs, reward, terminated, truncated, info
```

This environment is used both during training and evaluation phases, with different patient subsets (80/20 split). By combining real patient features with simulated motion dynamics, the agent is exposed to rich, varied data that mimics real-world clinical conditions.

Agent Training

To train the intelligent agent, we used the Deep Q-Learning (DQN) algorithm provided by the `Stable Baselines3` library. The agent's objective is to learn an optimal policy that recommends personalized gait rehabilitation interventions, based on the physiological and biomechanical state of a patient.

The environment was initialized using only the training portion (80%) of the dataset, and the agent interacted with this environment during 50,000 timesteps. The following code snippet shows the training setup:

```
from stable_baselines3 import DQN
from gaitLabEnv import GaitEnv

# Create training environment
train_env = GaitEnv(train=True, use_dof_model=True)

# Define and train the agent
model = DQN(
    "MlpPolicy",
    train_env,
    learning_rate=0.001,
    buffer_size=10000,
    learning_starts=1000,
    verbose=1
)
model.learn(total_timesteps=50000)
model.save("Models/gaitlab_dqn_model")
```

Listing 7.2: DQN agent training setup

The policy architecture used was a multilayer perceptron (`MlpPolicy`), suitable for low-dimensional input data. The learning rate and buffer size were chosen empirically to balance learning speed and stability. The reward signal was shaped to encourage correct predictions and penalize incorrect actions.

7.5 Model Evaluation

To assess the performance of the trained agent, we used a test environment consisting of 20% of the dataset not seen during training. For each patient instance, the model predicted the most appropriate rehabilitation recommendation based on the patient's state.

The predicted labels were compared against the true labels to compute several evaluation metrics commonly used in classification tasks:

- **Accuracy**: Measures the overall correctness of the model by calculating the proportion of correct predictions among all predictions made. It provides a general sense of performance but may be misleading if classes are imbalanced.
- **Precision**: Indicates how many of the predicted recommendations were actually correct. It is especially useful in medical contexts where false positives can be costly.
- **Recall**: Reflects how many of the actual recommendations were correctly identified by the model. It is important when minimizing false negatives is a priority.
- **F1 Score**: The harmonic mean of precision and recall, providing a balanced metric when both false positives and false negatives are relevant.

These metrics were computed using the `scikit-learn` library. A classification report and a confusion matrix were also generated to visualize the distribution of predictions across the recommendation classes. The confusion matrix helped identify specific areas where the model struggled or excelled, offering insights into its decision boundaries and potential biases.

```python
from stable_baselines3 import DQN
from gaitLabEnv import GaitEnv
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns

.....
# Compute evaluation metrics
acc = accuracy_score(true_labels, pred_labels)
prec = precision_score(true_labels, pred_labels, average='weighted', zero_division=0)
rec = recall_score(true_labels, pred_labels, average='weighted', zero_division=0)
f1 = f1_score(true_labels, pred_labels, average='weighted', zero_division=0)
.....
# Plot the confusion matrix
cm = confusion_matrix(true_labels, pred_labels, labels=env.actions_list)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=env.actions_list, yticklabels=env.actions_list)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix")
plt.tight_layout()
```

```
plt.show()
```

Listing 7.3: Evaluation metrics and Confusion Matrix plot

Chapter 8

Results

8.1 Training

The following figure shows the summary metrics obtained during the training phase of the DQN agent using Stable Baselines3. These indicators reflect the training process, stability, and efficiency of the learning algorithm. The model was trained for a total of 50,000 timesteps.

```
----------------------------------
| rollout/            |          |
|    ep_len_mean      | 1        |
|    ep_rew_mean      | 0.934    |
|    exploration_rate | 0.05     |
| time/               |          |
|    episodes         | 50000    |
|    fps              | 104      |
|    time_elapsed     | 478      |
|    total_timesteps  | 50000    |
| train/              |          |
|    learning_rate    | 0.001    |
|    loss             | 5.54e-05 |
|    n_updates        | 12249    |
----------------------------------
```

Figure 8.1: Training statistics generated by Stable Baselines3 after 50,000 timesteps.

8.2 Evaluation Metrics and Performance

To assess the performance of the trained Deep Q-Learning agent, we used a separate test set comprising 20% of the total dataset. The agent was evaluated on its ability to predict appropriate rehabilitation recommendations based on both biomechanical and clinical input features. The following classification metrics were computed using **scikit-learn** and were:

📋 Classification Report:

	precision	recall	f1-score	support
Improve posture	0.93	0.83	0.88	47
Maintain current routine	0.77	1.00	0.87	20
Rehabilitation exercises	0.70	0.64	0.67	11
Supervised training	0.90	0.90	0.90	10
Use assistive device	1.00	1.00	1.00	12
accuracy			0.87	100
macro avg	0.86	0.87	0.86	100
weighted avg	0.88	0.87	0.87	100

Figure 8.2: Classification report

In summary:

- Accuracy: **87%**
- Precision (weighted): **88%**
- Recall (weighted): **87%**
- F1 Score (weighted): **88%**

8.3 Confusion Matrix

To further visualize the performance of the agent, a confusion matrix was generated (Figure 8.3). It shows the distribution of predicted versus true rehabilitation recommendations, helping identify patterns in correct and incorrect classifications.

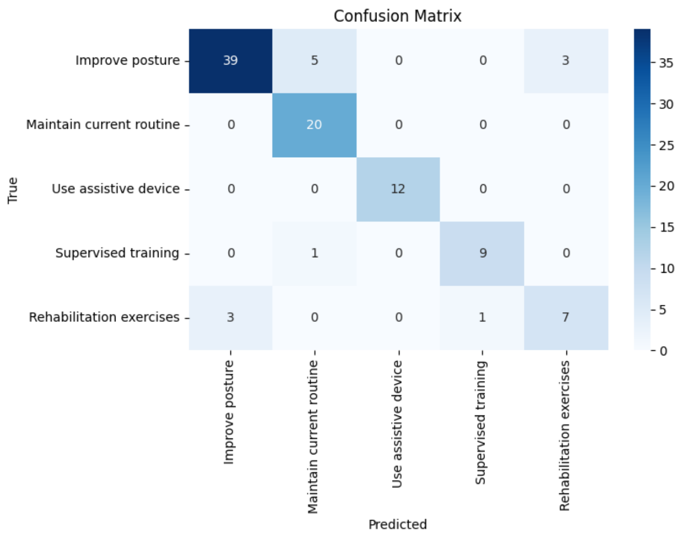

Figure 8.3: Confusion matrix comparing true recommendations and predicted actions.

8.4 Performance Analysis of the Agent

Figure **??** shows a visual summary of the agent's performance during evaluation on test patients. The bar chart on the left displays the number of correct and incorrect recommendations made by the model. The line plot on the right shows the reward obtained per patient. In addition, the **Acurracy** was **84%.**

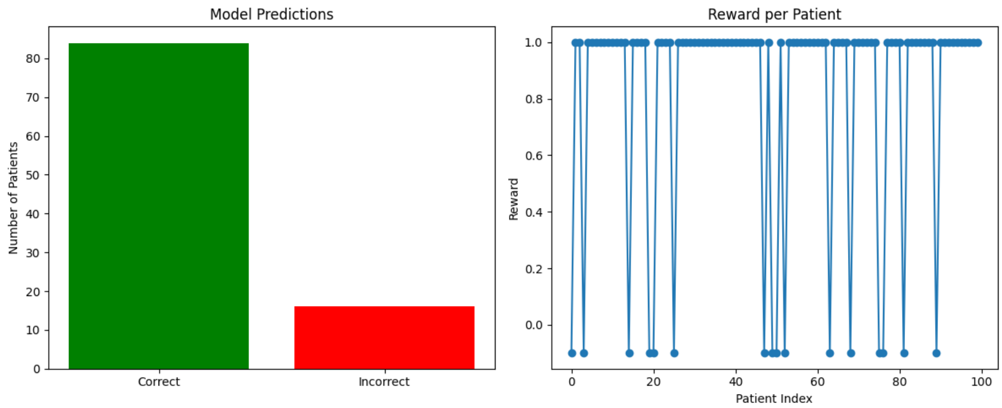

Figure 8.4: Left: Total number of correct vs incorrect predictions. Right: Reward received per patient based on the action taken.

8.5 Prediction Examples

A sample of the model's predictions for test patients is shown below:

```
Patient 1: True → Improve posture | Predicted → Improve posture
Patient 2: True → Maintain current routine | Predicted → Maintain current routine
Patient 3: True → Maintain current routine | Predicted → Maintain current routine
Patient 4: True → Improve posture | Predicted → Improve posture
...
Patient 18: True → Rehabilitation exercises | Predicted → Improve posture
...
Patient 23: True → Improve posture | Predicted → Maintain current routine
...
```

Chapter 9

Discussion

9.1 Training Metrics

The training log provided by the DQN algorithm includes several key indicators that help us interpret the learning behavior of the agent. Figure 8.1 shows some metrics very important to analyze.

The following metrics were extracted from the Stable Baselines3 DQN training log after 50,000 timesteps:

- **ep_len_mean = 1**: Each episode consisted of a single decision step. This behavior is expected since each patient constitutes an independent episode in which the agent provides a one-shot recommendation.
- **ep_rew_mean = 0.934**: The agent achieved an average reward close to 1.0 per episode, indicating that it was frequently selecting actions aligned with the correct rehabilitation recommendation.
- **exploration_rate = 0.05**: The agent had a low exploration rate at the end of training, reflecting a transition from exploration to exploitation, as the policy became more confident.
- **learning_rate = 0.001**: This moderate learning rate allowed for stable convergence during the training process without excessive fluctuations in loss.
- **loss = 5.54e-05**: A very low training loss demonstrates that the Q-network successfully minimized the prediction error between target and predicted Q-values, showing effective function approximation.
- **n_updates = 12,249**: This represents the number of weight updates performed. A sufficiently high number of updates ensures proper training coverage of the state-action space.
- **fps = 104, time_elapsed = 478 seconds**: These indicators confirm that training was computationally efficient, with over 100 frames per second and a total duration of under 8 minutes.

These training metrics suggest that the agent achieved a stable and efficient learning process. The high episode reward, low loss, and low exploration rate indicate that the DQN agent effectively learned a robust policy for recommending gait-related interventions.

9.2 Evaluation Metrics Discussion

To assess the performance of the trained agent, a classification report was generated using a separate test set (20% of the total data). The following metrics were computed (Figure 8.2):

- **Accuracy**: This metric calculates the proportion of correct predictions (both true positives and true negatives) over the total number of cases:

  $$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

  In the context of this project, accuracy represents the percentage of patients for whom the agent correctly recommended the appropriate rehabilitation strategy. An accuracy of 87% indicates that the model provided correct recommendations for most patients, demonstrating overall competence.

- **Precision (Weighted)**: Precision evaluates the proportion of correct positive predictions among all predicted positive cases:

  $$\text{Precision} = \frac{TP}{TP + FP}$$

  A weighted average is used to account for class imbalance. In this context, precision indicates how often the agent's predictions are correct when it recommends a specific action (e.g., "Improve posture"). A high precision of 88% suggests the model seldom makes unjustified recommendations.

- **Recall (Weighted)**: Recall, or sensitivity, measures the proportion of true positives that were correctly identified:

  $$\text{Recall} = \frac{TP}{TP + FN}$$

  This reflects the model's ability to detect all relevant cases. In our scenario, a recall of 87% means that the model correctly identified the appropriate recommendation for most patients who needed that specific advice.

- **F1 Score (Weighted)**: The F1 Score is the harmonic mean of precision and recall:

  $$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

  This metric balances precision and recall, especially useful when there is class imbalance. A weighted F1 score of 88% indicates that the model maintains a good balance between precision and recall, and handles various patient scenarios effectively.

These evaluation metrics demonstrate that the Deep Q-Learning agent is capable of making consistent and reliable recommendations. Its performance suggests that it generalizes well to unseen patients and can support rehabilitation guidance in a simulated gait laboratory setting.

9.3 Confusion Matrix Analysis

To further analyze the performance of the trained agent, we generated a confusion matrix, which provides a detailed breakdown of true versus predicted classifications for each rehabilitation recommendation category (Figure 8.3).

From the matrix, we can observe the following insights:

- **Improve posture**: Out of 47 total cases, 39 were correctly predicted, and 5 were misclassified as *Maintain current routine*, with 3 labeled incorrectly as *Rehabilitation exercises*. This indicates strong performance, though some confusion remains with less severe recommendations.
- **Maintain current routine**: All 20 instances of this class were correctly predicted, showing excellent precision and recall for this category.
- **Use assistive device**: All 12 instances were perfectly classified, demonstrating that the agent is highly effective at identifying this specific need.
- **Supervised training**: This class shows moderate performance. Out of 10 cases, 9 were correct, and 1 was misclassified as *Maintain current routine*. While not severe, it suggests slight overlap in decision boundaries.
- **Rehabilitation exercises**: This class had more confusion. Only 7 of 11 were correctly predicted. 3 were confused with *Improve posture* and 1 with *Supervised training*. This may indicate that the features defining this class are shared with other therapeutic interventions.

The confusion matrix highlights that the agent performs strongly across most categories, particularly for "Maintain current routine" and "Use assistive device." Some ambiguity remains between "Improve posture" and "Rehabilitation exercises," likely due to overlapping input features. Future work could explore refining the feature set or incorporating temporal patterns to improve class separability.

9.4 Prediction Accuracy and Reward Distribution

To complement the quantitative metrics, we visualized the model's prediction outcomes and reward signals obtained during evaluation (see Figure 8.4).

Bar Chart (Left): The bar chart illustrates the number of correct and incorrect predictions made by the agent across the test set. The model successfully predicted the correct rehabilitation recommendation for approximately 84 out of 100 patients, while around 16 cases were misclassified. This visual representation aligns with the accuracy value previously reported (87%), providing intuitive evidence of the model's robust performance.

Line Plot (Right): The reward distribution per patient demonstrates how well the agent performed on a case-by-case basis. The reward signal was binary (1 for correct action, 0 otherwise), and the plot shows high consistency, with most values at 1. Occasional dips to 0 represent incorrect actions or suboptimal recommendations. This behavior confirms that the reward function is effectively aligned with the model's objective: selecting appropriate therapeutic strategies.

Overall, these visualizations offer a clearer understanding of how the agent performs beyond aggregate metrics, highlighting its consistency and generalization capacity.

9.5 Limitations and Uncertainties

While the proposed gait laboratory agent demonstrates promising performance, several limitations must be acknowledged. First, the dataset used to train and evaluate the model was artificially generated, albeit with carefully crafted prompts to preserve consistency and realism among features. Nevertheless, synthetic data may not fully capture the complexity and variability present in real clinical scenarios, potentially affecting the model's generalizability. Second, although the agent's decisions are guided by Deep Q-Learning and shaped through simulated interactions, the absence of real patient feedback limits its capacity to adapt dynamically to unforeseen cases or nuanced patient conditions. Additionally, the reward structure, while useful for guiding agent behavior, is based on simplified assumptions about optimal recommendations and may not align perfectly with clinical best practices. Finally, the current evaluation does not incorporate temporal progression or long-term outcomes, which are critical in rehabilitation contexts. These factors highlight the need for future integration with real-world datasets, expert supervision, and longitudinal evaluation to improve robustness and clinical relevance.

Chapter 10

Conclusions and Future Work

10.1 Conclusions

This project successfully implemented a reinforcement learning agent for gait analysis using a systemic modeling approach and Deep Q-Learning algorithms. By integrating clinical and biomechanical information, the agent was able to generate personalized rehabilitation recommendations with a high level of accuracy. The system was trained on simulated patient data, which was generated using heuristic-based prompts to maintain coherence among features. This ensured that the training set reflected plausible patient profiles, enabling the model to learn meaningful patterns.

One of the most notable outcomes was the performance achieved by the agent during evaluation. The model reached an accuracy of 87%, a precision of 88%, a recall of 87%, and an F1-score of 88%, indicating consistent performance across various evaluation metrics. These results demonstrate the potential of reinforcement learning models to support decision-making in digital health environments, especially in contexts where structured patient data is available.

The use of reward signals and simulated environments based on degrees of freedom (DOF) models provided a realistic context for evaluating the agent's behavior. Furthermore, the design of the environment, including its state and action spaces, reflected a systemic understanding of gait dynamics, which contributed to the coherence and robustness of the agent's decision-making.

10.2 Future Work

Despite the encouraging results, this work also highlights areas for future research. The inclusion of real patient data would be essential to validate the system in clinical practice. Additionally, incorporating temporal information—such as gait evolution over time—could enrich the agent's understanding of patient progress. The reward system could also benefit from expert-driven calibration to better align recommendations with therapeutic goals. Finally, deploying the agent in interactive environments, such as virtual rehabilitation platforms, would allow for real-time feedback and broader applicability.

Additionally, collaboration with clinical experts could help refine the reward function and ensure that the system's decisions align with professional standards. Further development may also involve integrating additional sensors or physiological signals, expanding the action space with more nuanced interventions, and deploying the system within real or simulated clinical workflows to test its usability and impact in practice.

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