Workshop 3

Gait Laboratory Agent

System Sciences Foundations
Universidad Francisco José de Caldas

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1 Introduction

This workshop is a continuation of workshops 1 and 2, which were held during the course. First, corrections will be made and the recommendations given by the professor in previous workshops will be addressed. With this, the objective of workshop 3 focuses on integration with machine learning, cybernetic control mechanisms, multi-agent exploration, and preparation for the final delivery.

In Workshop 1, the laboratory agent system was designed, highlighting feedback loops, inputs, and expected outputs. Similarly, user stories were created and tools were identified to simulate and train the agent. With this in mind, this workshop continues to work on the designed system. It also improves the design of the feedback loops identified in the development of Workshops 1 and 2.

On the other hand, in Workshop 2, non-linear factors of the system were determined and used to design a causal diagram. This dynamic system takes into account characteristics that can affect the collection of patient gait data and, therefore, how these can affect recommendations. In addition, two more feedback cycles were identified, one within the system and the second describing a reward signal given by a specialist. Finally, a data structure and algorithms were developed to implement the dynamic behavior of the workshop. Considering this, this workshop continues to work on the concepts of a dynamic system. Also, a new mathematical model representing the patient's gait is added. Likewise, important concepts such as stability, convergence, inputs, expected outputs, and simulation scenarios are explained more clearly.

2 Feedback Loops

Feedback loops are important for ensuring greater efficiency in the system's recommendations. Based on the system diagram developed in previous workshops, internal and external feedback loops were identified. We will explore these in greater depth below.

2.1 Self-adjustment

This feedback occurs within the system, where the Insight Engine, which is an important component, is responsible for making recommendations and learns on its own. Therefore, it could be considered negative feedback, as it seeks to reduce errors in predictions and reach a point of stability. The aim is to ensure that the outputs (recommendations) made are relevant. The process carried out to make this feedback happen is illustrated in Figure 1. There, you can see that the Insight Engine is constantly evaluating itself internally in terms of how it makes recommendations based on data. The data can be analyzed by this engine to see how much certain parameters have changed, whether the patient has used the agent before, and how this compares to the current situation. In this way, it can improve and adjust its model, i.e., it would perform self-learning based on its own results.

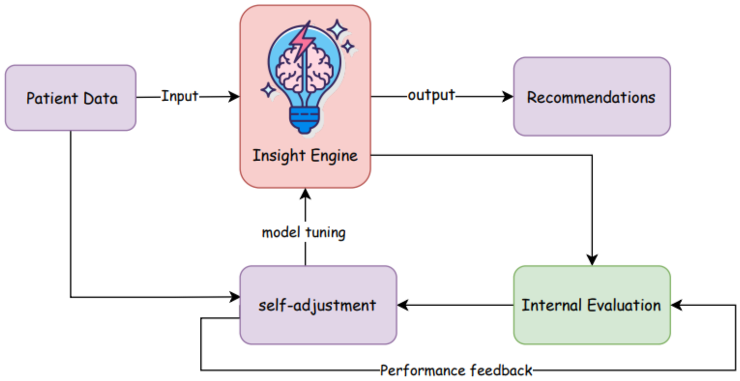

Figure 1: self-adjustment feedback diagram

2.2 Improved Patient's Performance

The main objective of our agent is to help patients improve their walking performance. By detecting anomalies in their gait, recommendations can be made that users can apply in their daily lives. Figure 2 illustrates this process, where each recommendation, in an ideal scenario, is applied to the letter by the patient. This feedback would be considered positive external feedback, as it occurs outside the system and changes the patient's behavior when they return to using the system. Their progress or deterioration can then be evaluated using the Insight Engine's self-adjustment feature. This is considered reinforcement learning, as the system will evaluate the effectiveness of the recommendations when applied in a real context. If it sees improvements, the model will continue to give those recommendations; if not, it will rethink them. In this way, the reward would be on a scale of 1 to 5, depending on how much the patient's gait has improved, and adjustments will be made accordingly.

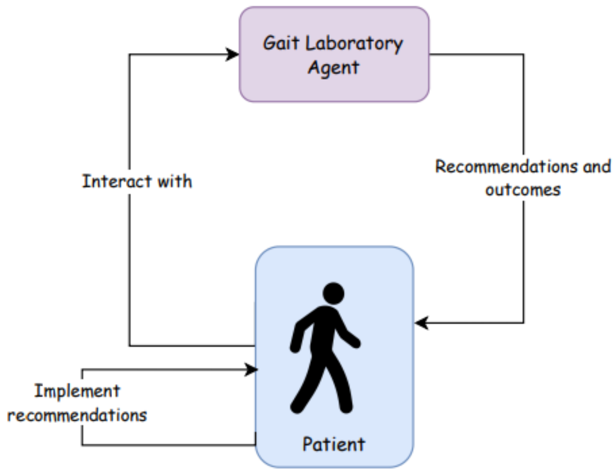

Figure 2: Improved Patient's Performance fedback diagram

2.3 Specialist's Reward

An additional feedback cycle involves a specialist or professional. As shown in Figure 3, this specialist analyzes the recommendations given by the agent in order to evaluate or rate them. In this way, external feedback is also provided, as it occurs outside the system. This feedback is positive because it involves an evaluation that corrects or reinforces the system, i.e., reinforcement learning.

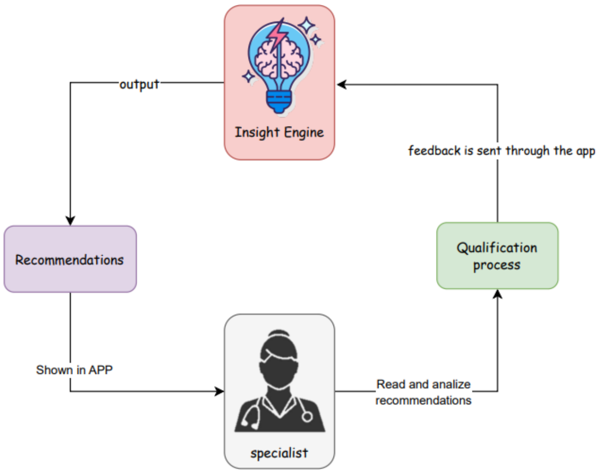

Figure 3: Reward Signal feedback diagram

3 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).

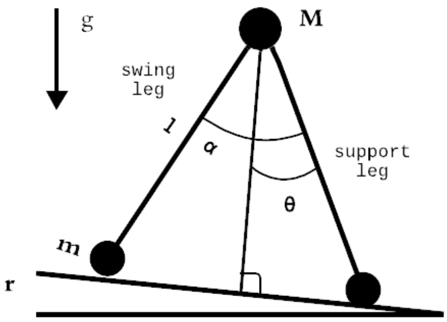

Figure 4: Double Inverted Pendulum Module

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.

$$\alpha = \frac{g}{l} * cos(\alpha) \tag{1}$$

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

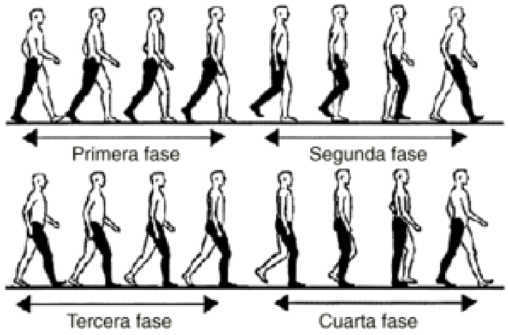

Figure 5: Phases of Human Gait

This model represents walking in a simple way based on a pendulum system (one supporting leg and one swinging leg), with the torso as the main mass. It helps us understand how the body balances and moves forward during walking, which can provide us with relevant information about patients' walking patterns. However, this model does not take into account muscle activation or joint flexion, which are other fundamental aspects for optimizing walking.

4 Machine Learning Implementation

4.1 Algorithms and Frameworks

The incorporation of reinforcement learning (RL) techniques allows us to design intelligent agents capable of learning directly from experience in order to intervene in an optimal and personalized way in each patient's progress. Therefore, the use of Q-learning and its version based on deep neural networks, Deep Q-Networks (DQN), opens up new possibilities for the construction of agents and, in this case, autonomous and adaptive recommendation systems.

First, the Q-learning algorithm allows an agent to learn an optimal policy to maximize long-term cumulative rewards. The network learns from a function $Q(s, a)$ that estimates the expected value of performing an action a in a state s, and then follows the most beneficial policy. However, for the gait laboratory, this algorithm is not very viable, given that gait analysis is a complex task. In which, a large number of variables influence the gait of patients.

Secondly, the DQN algorithm overcomes the limitations of Q-learning by replacing the Q table with a deep neural network that estimates the Q values directly from state observations. In the case of the walking laboratory agent, the network takes a vector of physical characteristics (kinematic, kinetic, and electromyographic) extracted in real time using sensors (angles, lengths, or flexions) and predicts the Q values for each possible action (recommendations). In healthcare, DQN can be used to personalize treatment plans by learning from patient data and maximizing long-term health outcomes.

On the other hand, to implement the DQN algorithm, we must take into account the following components: Environment status: a compact but informative representation of the patient's progress must be described. Then, possible actions: define the interventions that the agent can perform. Also, feedback: this must quantitatively represent how good the action was in relation to the objective. Importantly, the algorithm is chosen and training proceeds. At this point, the algorithm will already have been implemented.

With this in mind, the following libraries are taken into account for the implementation of this algorithm and the creation of the agent at the code level:

- **Stable-Baselines3:** It is used to quickly train an RL agent (such as DQN, PPO, A2C, SAC) in a customized environment. It is also ideal for prototypes and controlled clinical applications. Finally, it is very useful for simulating walking sessions before applying it to real patients. In our context, to use it we would need to define a walking environment as a Python class compatible with Gymmnasium. Specify observations (state), actions, and reward index. Have real-time or simulated input data.
- **PyTorch :** It is used to create custom neural networks to approximate functions $Q(s, a)$ or policies. It is ideal when you want to have complete control over the architecture or use more complex data. In our context, we would need preprocessed input data, define the neural network, and a training loop that interacts with the environment.

- **TensorFlow:** It is used to build and train neural networks. It also allows you to use TensorBoard to visualize metrics in real time. In our project, we need to prepare training data, define the model with Keras, and integrate the model into the RL loop or use it in a framework such as $TF-Agents$.

Cybernetic Feedback Integration

To ensure that the reinforcement learning agent aligns with the dynamic design of the gait system, a precise mapping between sensor inputs and the reward function is established. The agent receives multimodal input data from both the kinematic and dynamic modules:

- **Kinematic module :** provides body position and joint angle data via electrogoniometers, cameras, and optoelectronic sensors.
- **Dynamic module**: delivers muscle activity, ground reaction forces, joint moments, and electric potentials through EMG, force platforms, and transducers.

The mapping (Table 1) enables the agent to evaluate the impact of its recommendations through a reward signal derived from observable outcomes. For example, electrogoniometers and force platforms quantify joint behavior and load distribution, while EMG measures the efficiency of muscle recruitment. Deviations from ideal patterns trigger penalties, whereas improvements yield positive reinforcement.

Furthermore, data from medical history and environmental sensors introduce adaptive mechanisms in the reward structure. These inputs allow the system to adjust expectations based on prior injuries, neurological conditions, or external factors like poor visibility or signal noise.

By integrating this sensor-to-reward mapping into the learning process, the agent builds a feedback loop that reinforces beneficial gait corrections while discouraging maladaptive patterns. This design ensures that the reward system not only reflects biomechanical realities but also supports convergence toward clinically meaningful outcomes.

5 Agent Testing and Evaluation

To verify that the agent is functioning properly, it is necessary to understand the possible scenarios that may arise when the agent is used. This is in order to validate how the agent is learning under different conditions. It is also extremely important to be clear about the metrics needed to train the agent and enable it to learn.

5.1 Experimental Setup

In order to validate the robustness of the agent under various conditions, the following test scenarios are defined and organized into categories:

Physiological conditions of the patient

- Patient without disturbances, with normal biomechanical parameters.
- The patient presents a physical injury that negatively affects their gait pattern.
- The patient has performed physical activity prior to the session, which may cause muscular fatigue and influence gait quality.
- The patient has consumed a substance (food, medication, etc.) that impairs balance or motor coordination.
- The patient is drowsy due to lack of sleep, which can alter postural stability.

Environmental conditions

- The sensors, cameras, and platform are in optimal condition and correctly positioned.
- The lighting level is insufficient, preventing the cameras from accurately capturing the patient's movement.
- There are communication failures between the system's hardware and software, possibly due to electrical interference or external environmental factors.
- The walking platform presents stability variations, which can affect the precise measurement of angles and biomechanical metrics.

Sensor/Source	**Input**	**Detected Pattern**	**Reward**
Electrogoniometers	Joint angle (knee, hip)	Limited range of motion or asymmetry between legs	+1 range or symmetry improves –1 restricted
Cameras	Body coordinates (trajectory)	Deviation from a straight walking path	+1 follows ideal path –1 deviates
Cameras / timing sensors	Time between gait events	Unstable rhythm or phase asynchrony	+1 coordinated cycle –1 irregular timing
Force platform	Ground reaction forces	Uneven weight distribution / excessive impact	+1 balanced load distribution –1 overload or imbalance
Force platform	Joint moments	Abnormal biomechanical compensations	+1 compensations corrected –1 compensations persist or worsen
EMG (Electromyography)	Muscle activation	Inefficient or delayed muscle recruitment	+1 efficient muscle synchronization –1 abnormal or desynchronized activity
Medical history (digital format)	Previous injuries	Reappearance of risk patterns or overload	Penalty if harmful patterns are repeated
Medical history	Neurological diagnosis	Anticipated difficulty in coordination or stability	Adjustment based on expected limitations
Medical history / sensors	Medication affecting motor function	Possible interferences or unexpected gait pattern variations	Penalty/Adjustment if movement is altered by medication
Environmental sensors / cameras	Image quality / environment	Low visibility or electric noise affecting data acquisition	Penalty proportional to capture error
Specialist (human evaluator)	Recommendation evaluation	Relevant / partially useful / inadequate	+1 recommendation is relevant 0 partially useful –1 inadequate suggestion

Table 1: Mapping of sensor inputs, detected gait conditions, and corresponding reward signals.

Usage history and feedback

- The patient has previously used the gait laboratory without showing significant improvements in their walking pattern.
- The patient has shown clear improvements after previous sessions in the gait laboratory.
- The specialist considers that the agent's recommendations are appropriate and useful.
- The specialist considers that the agent's recommendations are inadequate, suggesting the need to adjust the model's policy.

5.2 Performance Metrics

To evaluate the effectiveness of the agent and the impact of its recommendations on patient progress, both general reinforcement learning metrics and specific biomechanical and clinical domain metrics are considered.

Biomechanical and clinical metrics

- **Energy expenditure:** Measures the amount of metabolic energy used by the patient while walking. It helps detect how efficient the gait is, as ideally less energy should be consumed.
- **Time between events:** Measures the duration between key gait cycle events, such as the time between knee flexion and extension, time between heel strike and toe-off, and time between the stance and swing phases. These times are measured through sensors, the camera, and the platform. This metric helps assess the patient's coordination and rhythm, which may indicate neuromuscular dysfunction or fatigue.
- **Gait symmetry:** Measures the degree of similarity between the actions of the left and right leg during walking. Alterations in symmetry may reveal biomechanical compensations, muscle injuries, or neurological disorders. To quantify this phenomenon, a symmetry index proposed by Robinson et al. (1987) can be used. This index expresses the relative difference between the values recorded in each leg as a percentage of their average. Its formula is as follows:

  $$SI = \left| \frac{V_{right} - V_{left}}{\left(\frac{V_{right}+V_{left}}{2}\right)} \right| \times 100$$

  Where:

  - V_{right}: Value of the measured variable in the right leg.
  - V_{left}: Corresponding value in the left leg.

  An SI value of 0% indicates perfect symmetry, while higher values represent greater asymmetry.
- **Balance control:** Measures the level of balance control during walking. It is evaluated through the variation of the center of mass and its relation to the base of support, as well as lateral and anteroposterior oscillations of the trunk or pelvis. Force platform, sensors, and camera data are also considered. This metric is crucial, as unstable gait may lead to unexpected falls or injuries.
- **Deviation from ideal gait path:** Measures how far the patient deviates from the ideal or straight walking trajectory. It can be obtained by tracking the position of the body or feet throughout the walking path. The inverted pendulum model, discussed earlier, can be used to estimate dynamic balance and optimal path. Significant deviations may indicate balance issues, fatigue, or muscle weakness.
- **Patient improvement rate:** Measures the patient's progress over multiple gait sessions. It can be assessed by comparing historical metric values. This allows evaluating whether the recommendations given to the patient are effective and shows whether there is positive or negative evolution in their gait pattern.
- **Recommendation agreement:** Measures the level of agreement between the agent's suggestions and those made by the specialist. The specialist reviews the system's recommendations and classifies them as relevant, partially useful, or inadequate. This metric helps validate the system's reliability, adjust the agent's learning policy, and build trust in the use of the gait laboratory.

Learning Curve

Learning Path

The proposed learning path for the gait agent includes progressive stages that the agent follows in order to learn how to generate useful recommendations.

1. **Information Gathering:** The agent receives the patient's biomechanical data, obtained through sensors and the camera. The data is then organized and prepared for the agent to use.

2. **Evaluation of Internal and External Conditions:** The agent identifies factors affecting gait, based on the metrics described in the previous section.

3. **Recommendation Delivery:** The agent suggests adjustments to improve the patient's gait.

4. **Feedback Reception:** An internal evaluation is carried out to measure the effect of the recommendations on key metrics. Additionally, the specialist assesses the relevance of the suggestions. The agent then receives positive reinforcement if the patient shows improvement or if there is alignment with the specialist's judgment.

5. **Adjustment of Decision Strategies:** Based on the feedback received, the agent adjusts its learning strategies, improving the quality and precision of its recommendations.

Stability and Convergence

In the context of the gait laboratory, the agent's stability and convergence are essential to ensure that its recommendations remain reliable and useful over time.

For this reason, the gait agent is designed to exhibit **BIBO Stability (Bounded Input, Bounded Output)**. This type of stability ensures that if the inputs are bounded, the outputs will also be bounded. In this case, the inputs consist of physical and biomechanical patient data, which are naturally limited. Thus, the recommendations are expected to remain within reasonable bounds, avoiding abrupt or out-of-context suggestions.

Regarding convergence, the agent uses reward signals to learn which actions are beneficial. As it gains experience, its decisions are expected to become more consistent, and its errors to decrease. This process indicates that the system is **converging** toward stable and effective learning. Signs that such convergence is occurring include:

- The patient's biomechanical metrics show improvements.
- The number of recommendations rejected by the specialist decreases.
- The agent's behavior tends to repeat under similar conditions, indicating learning.

Figures 6 and Figure 7, illustrate the expected convergence in terms of reduced recommendation errors and improved gait performance as the number of sessions increases or as the agent gains experience.

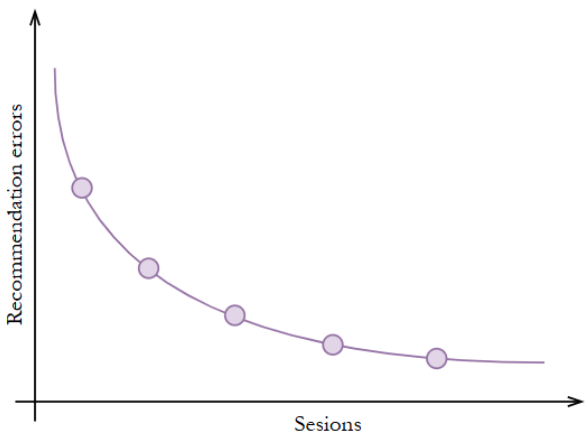

Figure 6: Sesions vs. Recommendation errors

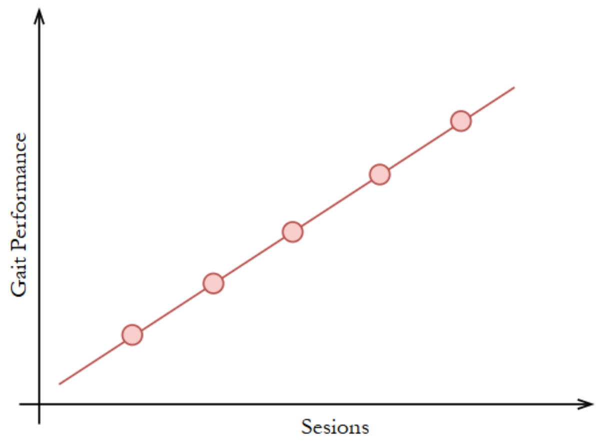

Figure 7: Sesions vs. Gait Performance

It is important to consider both stability and convergence, as their absence may lead to system instability. This can result in dangerous, unreliable, or contradictory recommendations, compromising the patient's gait and overall health. Moreover, without convergence, the agent's decisions will show excessive variability, preventing effective learning from experience. Another critical issue is the potential loss of patient trust, especially if inconsistencies cause confusion or discourage continued use.

As a conclusion, another key metric is the **convergence speed**, which measures how quickly the agent is able to stabilize its recommendations and minimize learning errors. This can be quantified by observing how many sessions are needed for the agent to reach a stable and optimal performance. Convergence speed is often visualized through a learning curve or cumulative error curve over time.

A high convergence speed is desirable because it enables the agent to learn effectively with less data, shorter training time, and reduced specialist intervention. It also means the gait lab can produce meaningful results in fewer sessions, increasing its usefulness and the trust it inspires.

6 Mono-Agent

The gait laboratory is classified as a single-agent system, as its operation is centered on a single user who interacts directly with the system. The agent is responsible for capturing, processing, and interpreting the individual's biomechanical data in real time, and for generating diagnoses or suggestions to improve their performance.

Although a specialist may intervene by evaluating the results provided by the system and offering additional feedback, this participation is complementary and external to the main agent. There is no cooperation or interaction between multiple intelligent agents, nor is there any attempt to model group behavior or complex interactions between users.

Therefore, as it is an individualized environment, with a single source of perception, decision-making, and automated action, it is fully justified to consider it a single-agent system, in which any human feedback serves as external reinforcement or validation, and not as an integral part of the agent's decision-making process.

7 Future Work

As future work, the main objective will be to design and fully implement the walking laboratory agent, integrating everything developed in the previous workshops. In the design stage, the agent's architecture will be precisely defined, including state spaces, actions, and rewards, as well as the selection of the most appropriate reinforcement learning algorithm (e.g., DQN). This phase also includes the design of the simulation environment compatible with Gymmnasium, where different clinical scenarios will be recreated to train the agent without real risks.

In the implementation phase, the agent will be trained using specialized libraries such as Stable-Baselines3, PyTorch, or TensorFlow, employing simulated or historical gait data to accelerate learning. Subsequently, the agent's behavior will be validated in controlled sessions, evaluating its stability, convergence, and the quality of its recommendations. This division between design and execution ensures that the agent is properly grounded before its application in real time or with real patients, thus ensuring safe, adaptive, and reliable clinical results.

References

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