Iterative Design Outline of Gait Laboratory Agent

Carlos Andres Celis Herrera - 20222020051

Xiomara Salomme Arias Arias - 20222020028

Universidad Distrital Francisco Jose de Caldas

System Sciences Foundations

Carlos Andres Siera

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Dynamics Systems

Dates Structures

Data is an essential part of the project, from the use for motor training, processing and gait analysis. Therefore, a good use of this data leads to fulfill the objective of the system. With this in mind, the structure of our data is as follows.

- Physical data

Physical data						
Electric potentials	Forces	Moments	Muscle activity	position	Weight	height

- Medical history

Medical history			
AgePacient	injuries	laterality	Constraints

- Experiences Buffer

Experiences Buffer			
Experience	datosCuadros	feedbackLoop	Predictions

On the other hand, these system data structures can be stored in hash tables in order to efficiently store and retrieve data. The main idea of hash tables is to associate keys or keys with values by means of a hash function. A hash function is a mathematical operation that converts any input into a fixed-length output, called a hash or hash code. The hash code is used as an index to store and access the value in an array, called a bucket.

Algorithms

- **Kalmar Filter Algorithm:** The Kalman filter is a recursive estimation algorithm that improves the prediction of hidden or noisy variables from a combination of theoretical models and empirical measurements. In the context of sports science, this filter has proven to be a powerful tool for estimating variables such as fitness, fatigue or motor performance from incomplete or noise-affected data, such as from portable sensors (IMU, GPS, EMG). According to Pathak (2021), the usefulness of the Kalman filter lies in its ability to optimally integrate prior knowledge of the system (dynamic model) with noisy observations of the environment, adjusting in real time the prediction of the state of the athlete or biomechanical system. This makes it an ideal resource for intelligent agents that need to adapt their decisions to the evolution of the user's internal state, such as in gait laboratories.

Figure 1 shows the diagram of the Kalman Filter algorithm, it is very useful to understand how to implement it in the context of the March Lab.

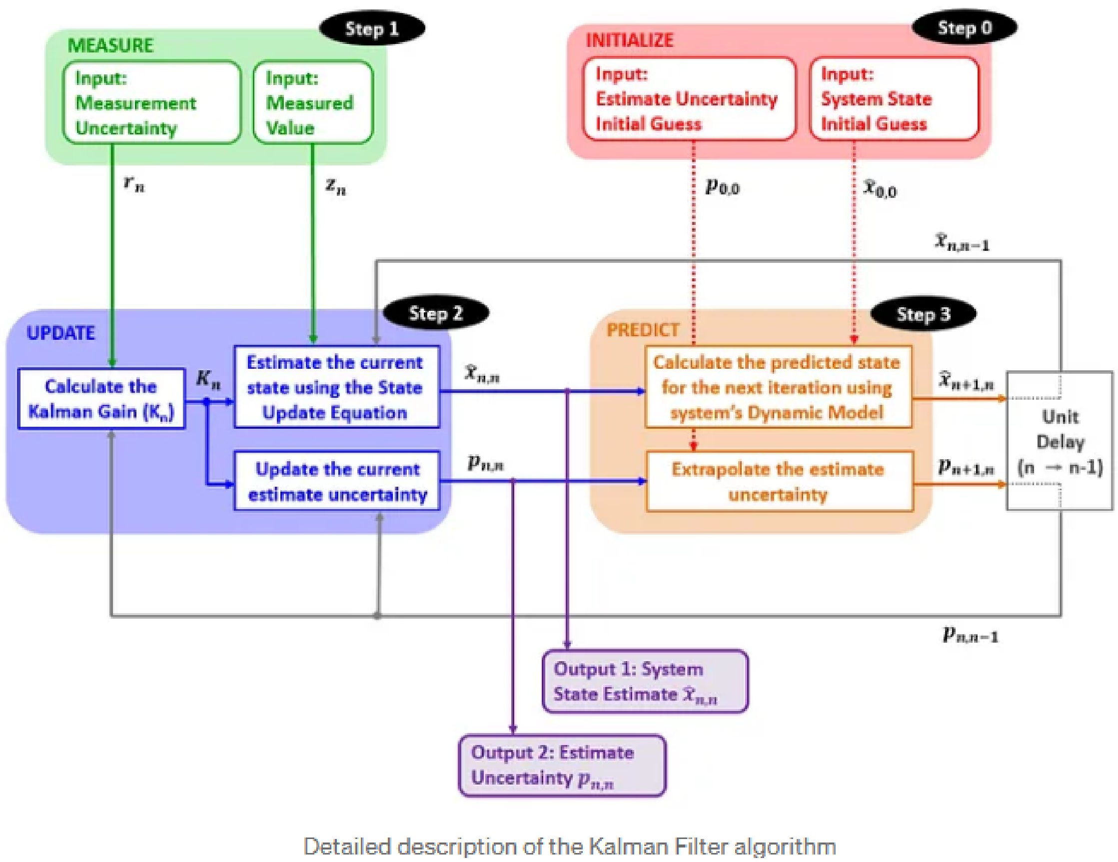

Figure 1

Detailed description of the Kalman Filter algorithm

- **Deep Q-Learning (DQN):** The Deep Q-Learning (DQN) algorithm is an extension of classical Q-learning that uses deep neural networks to approximate the action-value (Q) function, allowing it to scale to environments with continuous and complex state spaces. Instead of storing a table of Q-values for each state and action, DQN employs a neural network that predicts the Q-values for all possible actions given the observed states. This technique has been key in successful applications of reinforcement learning, such as the control of autonomous agents in video games or recommender systems.

In the context of an adaptive agent in a gait laboratory, DQN could allow the system to learn, by experience, when and how to optimally intervene in a patient's gait, based on the perceived biomechanical state and reward signals defined by improvements in symmetry, efficiency or stability. Thus, the agent could develop a personalized adaptive policy that improves over time, even in the presence of variability between users or clinical conditions Kukreja (2020).

Frameworks

To dynamically model the patient's gait system, a framework can be implemented that combines **SimPy**, a discrete event simulation library, with **Gymnasium**, a reinforcement learning environment. In this scheme, **SimPy** would be in charge of simulating the passage of time and the evolution of variables such as fatigue, rest or the quality of recommendations, making it possible to represent nonlinear and time-dependent behaviors. For its part, **Gymnasium** defines the decision-making environment of the agent (e.g., the personalized recommendation system or the analysis engine), which takes actions based on observations of the simulated environment and receives rewards based on the effectiveness of the intervention or the improvement in the patient's progress. This integration makes it possible to train adaptive agents under realistic and stochastic conditions, evaluating policies that optimize the system's long-term performance.

Dynamic test

- **Simulation parameters**: The simulation of the system begins with a series of sensors that measure different aspects of gait, some of these are: optoelectronic sensors, electrogoniometer sensors, reinforcement platforms, transducers, among others. By means of these important physical parameters of the patient's gait are measured, these should be the next to be simulated, since they are the input of the system and with which a subsequent analysis will be made to determine the patient's condition.

- **Scenario variations**: They are different types of scenarios in which parameters change between them, but without losing the central context. For example: User with knee injury, his gait will not be the best and the system will generate more recommendations; Healthy and rested user, his gait will be more controlled and he will not get tired so much, the system may not give many recommendations. As well as these two particular cases, there are many more scenarios where the mere fact of changing a parameter such as: increasing the weight, speed or time during walking, generates different scenarios to analyze but without losing the context that is to optimize the gait.

References

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Pathak, S. (2021). *Kalman filter in sport science.* Retrieved from `https://swetankpathak.medium.com/kalman-filter-in-sport-science-3df199d10d5b` (Accessed: 2025-05-08)