PhD Thesis

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Development and implementation of active safety systems in vehicles using spiking neural networks

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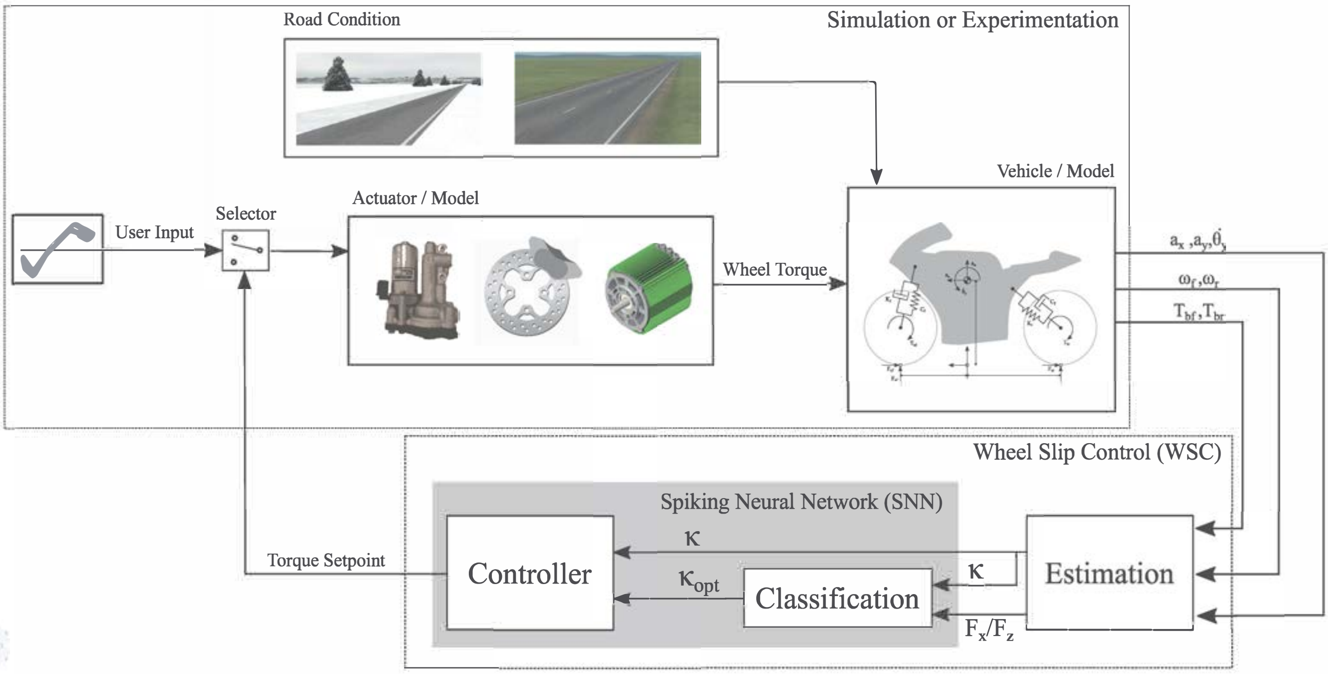

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University of Málaga
Department of Mechanical Engineering and Fluid Mechanics

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JAVIER PÉREZ FERNÁNDEZ

MÁLAGA, 2021

DECLARACIÓN DE AUTORÍA Y ORIGINALIDAD DE LA TESIS PRESENTADA PARA OBTENER EL TÍTULO DE DOCTOR

D./Dña JAVIER PÉREZ FERNÁNDEZ
Estudiante del programa de doctorado INGENIERÍA MECÁNICA Y EFICIENCIA ENERGÉTICA de la Universidad de Málaga, autor/a de la tesis, presentada para la obtención del título de doctor por la Universidad de Málaga, titulada: DEVELOPMENT AND IMPLEMENTATION OF ACTIVE SAFETY SYSTEMS IN VEHICLES USING SPIKING NEURAL NETWORKS

Realizada bajo la tutorización de JUAN ANTONIO CABRERA CARRILLO y dirección de JUAN ANTONIO CABRERA CARRILLO Y JUAN JESÚS CASTILLO AGUILAR

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Que las publicaciones que avalan la tesis de JAVIER PÉREZ FERNÁNDEZ titulada "DEVELOPMENT AND IMPLEMENTATION OF ACTIVE SAFETY SYSTEMS IN VEHICLES USING SPIKING NEURAL NETWORKS" no han sido utilizadas en tesis anteriores. Y que ha alcanzado los objetivos de investigación propuestos, estando debidamente cualificada para su defensa.

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En Málaga, a 31 de AGOSTO de 2021

University of Málaga
Department of Mechanical Engineering and Fluid Mechanics

PhD Thesis

Development and implementation of active safety systems in vehicles using spiking neural networks

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Málaga, 2021

"Al carro de la cultura española le falta la rueda de la ciencia"
Santiago Ramón y Cajal, 1852-1934

Abstract

In this thesis, a new control algorithm based on biological neural networks to maximize longitudinal forces in the tire-road contact in emergency situations while driving with ground vehicles is proposed. This thesis has been funded by the Ministry of Universities through the university teacher training grant (FPU17/03161) awarded to the author in 2018. The thesis has had a total duration of 3 years. In the initial report delivered to the Ministry, the thesis was planned to last 4 years, assigning the last year to the drafting of conclusions of the thesis. However, it has been possible to carry out the whole work in three years.

The thesis is presented in the form of a compilation of publications. This way, four papers published in high-impact journals supporting the research are presented, describing the required methodology for the implementation of a bio-inspired controller in a vehicular system. In addition, the International PhD Mention will be obtained since a three-month stay in a research group of a foreign university has been carried out by the doctoral candidate.

Furthermore, the author of this thesis has participated as a collaborator in the following research projects, related to the subject of the thesis:

- "Real-time determination of the characteristics of the tire-road contact using bio-inspired algorithms for the improvement of active safety in vehicles" (TRA2015-67920-R). During the two years before enrolling in the doctoral program the foundations of the thesis was established. The relevance of the control algorithm in an emergency was highlighted during this period.
- "Regenerative braking system based on bio-inspired algorithms" (UMA18-FEDERJA-109). Started during the execution of the FPU grant and continues at present.
- "Road type identification methods based on neural networks for electric vehicles" (PID2019-105572RB-I00). Started during the execution of the FPU grant and continues at present.

This thesis was linked to the goals of these research projects since they focused on improving vehicle efficiency and safety by resorting to advanced control and estimation algorithms. In this sense, bio-inspired algorithms and neural networks were developed to tackle the challenges of these projects. Vehicle control is also a key factor in projects where the behavior between the tire and asphalt is under study. This thesis focuses on the longitudinal control of a vehicle, where, by managing a torque applied to a wheel, either by braking or traction, the force obtained during contact is maximized.

Once the starting point and the context of the thesis have been outlined, the main problems to develop an optimal control methodology are described next. First of all, the great importance of estimating the forces in tire-road contact with a high degree of accuracy, since the stability of the vehicle depends on them, has to be highlighted. These contact forces show clear non-linear behavior. Furthermore, there are also variations due to the environment in which the vehicle is being driven. On the other hand, the main variable related to the level of adherence experienced by a tire when rolling on a surface is the slip, which can be defined as the speed difference between the wheel and the vehicle. Thus, vehicle speed has to be known to obtain the slip. However, vehicle speed is a parameter that is still difficult to measure in today's vehicles. In addition, tire models are also affected by other parameters that influence their response, such as temperature, wear, tire pressure, etc.
Therefore, developing a controller capable of managing all data and variables in the tire-road contact is a complex task that requires algorithms that can deal with all possible driving scenarios at a reasonable computational cost. As a solution to this problem, a control algorithm capable of adapting to unexpected conditions dynamically is proposed in this work. To achieve this objective, as in other engineering problems, the answer lies in nature. Thus, the developed control algorithm is based on the nervous system of living beings in the form of a bio-inspired control structure capable of learning during its normal operation.
The description of the global scheme used is required to understand the requirements for the development of a longitudinal vehicle control algorithm. The controller has to adapt to the current tire-road adhesion and has to provide the control actions required to maximize the longitudinal forces, thereby avoiding wheel locking. The main components of such a control scheme are:

Model	Vehicle Tire-road contact Actuators
Algorithms	Parameter estimation Identification of adhesion conditions Controller
Measurements	Parameter measurement

Therefore, the following requirements should be incorporated in each of these components to accomplish the required task:

-Vehicle: Load transfer and degrees of freedom.
-Tire-road contact: Non-linear friction.
-Actuators: Time response.
-Parameter measurement: Resolution and delays
-Parameter estimation: Dynamics of the vehicle and delays.
-Identification of adhesion conditions: Data required.
-Controller: Fast response and adaptation capabilities

The vehicle model should take into account the load transfer that takes place when accelerating and braking as well as having a sufficient number of degrees of freedom to reproduce the main vehicle's movements adequately.
Regarding the tire model, it has to be a non-linear function of the slip to properly reproduce tire-road friction. In addition, its transient response should also be included since the delay in the appearance of friction forces should be considered. To this end, the relaxation length is utilized to model the transient response. The model used should also take into account the influence of environmental conditions, such as temperature, pressure, humidity, road type...
Regarding parameter measurement and estimation, it is crucial to consider the delays introduced by the sensors, as well as their resolution. For example, the encoders used to measure the angular velocity of the wheels have a reduced number of pulses per revolution, which at low speeds can lead to problems in detecting wheel locking. Besides, the slip value is required to estimate the adhesion conditions. In order to obtain the slip value, the speed of the wheels and the speed of the vehicle's body have to be determined. The latter cannot be measured directly using in-vehicle sensors at a reasonable cost. In addition, other technologies for speed measurement, such as those based on the Global Positioning System (GPS), cannot be used in this case due to the delay in their measurement. Therefore, vehicle speed is obtained by combining data fusion and estimation algorithms. This is usually solved by using Kalman filter-based algorithms and by measuring system variables such as the accelerations captured by the Inertial Measurement Unit (IMU). This task is performed by taking into account the dynamics of the vehicle in such a way that the state variables can be defined.
Once the longitudinal speed of the vehicle and the slip have been obtained, the identification of the type of road, where the vehicle circulates, is of vital importance. Road type detection is a subject of continuous study. For now, a standardized solution has not been proposed yet. There are two main ways to cope with this challenge. The first approach to accomplish this task is based

on the knowledge of tire dynamics. In this case, the main problem to tackle is that the tire model used must be capable of characterizing all possible driving conditions, including the influence of all the parameters that affect the tire. This makes the implementation of this strategy challenging due to the amount of data required to build the model and the associated model complexity, which hamper its implementation in real-time applications.The second method resorts to neural networks to perform the road type classification task. These structures can replicate the tire model and establish the relationship between the type of road and other variables measured in the vehicle, such as vibrations or a video camera capturing the road. The methodology proposed in this thesis falls in this second approach. Thus, the same structure of neural network used to perform control tasks is used to identify the road type.

Next, the actuators are responsible for converting the control action into forces that modulate the wheel slip. In this sense, the challenge is to achieve a fast and reliable performance, since the locking of a wheel is a process that can take place in less than 200 milliseconds. The overall behavior of the system performance can be reduced if the modeling of the actuators is not properly addressed. In the case of different actuation modes, for example in electric vehicles with friction and regenerative braking, an optimal strategy will have to be defined.

The last component is the control algorithm, which is responsible for providing the required action on the vehicle. The control algorithm must be capable of regulating the wheel torque to keep the wheel slip close to its optimum value according to the tire-road contact conditions. To this end, it must be able to recognize and adapt to the varying driving conditions, making use of the estimated slip level and the desired optimal slip value. The actuation might involve regulating the torques applied to the wheels, employing an actuator. The most commonly used controllers are based on Sliding Mode Control (SMC), fuzzy logic, and Model Predictive Control (MPC). This thesis resorts to a biologically-based neural network that, unlike the previous controllers, can adapt to changes in the dynamics of the contact during the execution of the algorithm. This way, if the vehicle is facing an adhesion condition that has never been experienced before, the control algorithm will adapt itself thanks to a learning strategy to maximize the longitudinal forces and hence, avoid wheel locking.

Out of all the components involved in the wheel slip scheme, the control algorithm has the greatest impact on the final performance. Therefore, research efforts have been focused on the development of an optimal algorithm. In this respect, humans have proven to have a superior ability to control the dynamics of tire-road contact: pushing a vehicle to its grip limits in a controlled and safe manner is the main objective of any motor racing competition. In this case, the aim is to maximize grip, usually to reduce the time needed to cover a fixed distance, maintaining the stability of the vehicle. Professional drivers' ability to adapt to a new vehicle, as well as the detection of the limit of adherence in changing conditions (new tire compound, circuit, weather conditions, etc.) is remarkable.

As it has been shown, the optimal control of complex systems in changing operating conditions is a challenging task that requires an adequate performance of the different components of the control algorithm. However, living beings cope with these problems continuously and solve it properly in most cases.

The strategy developed in this thesis is based on the study of motor control in biological systems. In the first place, we attempt to understand how the neural connections of a human being or animal determine the response to external stimuli and allow correcting the error made. In the case of tire contact, human beings are capable of adapting the percentage of gas or braking according to sight, accelerations experienced by the semicircular canals, sounds, and so on. Nonetheless, human beings do not know the level of slippage in every moment. This is the advantage of electronic control, since it can be provided with this key information to achieve similar results to those of a trained human being using a simpler control structure. To this end, the definition of the control structure requires modelling biological systems adequately.

The study of biological control allows understanding how neural connections are established. There are two theories regarding the possible control schemes in biological systems. The first one resorts to an internal model of the system to be controlled. This implies a high level of knowledge of the system's dynamics, limiting the learning capacity due to the fact that the internal model has to be modified to adapt to variations. The second theory is based on threshold control whereby, without the need for an internal model, an equilibrium point is established. When this point is exceeded, a control action takes place. Thus, by modifying the equilibrium point, a biological system can be controlled. Neural connections are changed to maintain the equilibrium in the working point. While the internal model theory implies a complex control structure, which is difficult to decode, the threshold control theory presents a simple structure that only requires a neural path to maintain equilibrium.

The latter theory, called the Equilibrium Point Hypothesis (EPH), is the one applied in this thesis. Therefore, through the study of biological structures in humans and animals, it is intended to find those that show similar behavior as predicted by the EPH. Kandel's works were the basis to obtain the control structure as well as the learning mechanisms involved in living beings. For this purpose, he used Aplysia, an animal that has a very large neuron size, which facilitates its decoding. Subsequently, many other animal structures have been

decoded. In humans, it has been possible to determine certain control structures, for example, some associated with reflexes, called reflex arcs. Even so, the vast majority of the human brain and nervous system is still unknown and represents a great technical challenge due to the high number of neurons and connections that compose such an intricate structure.
From the study of the reflex arcs, it is possible to establish the overall behavior of the neural network in charge of control. For example, in the vestibulo-ocular reflex, continuous control of the gaze is maintained using the accelerations measured by the semicircular canals. The structure that handles eye movement sets the neural pathways from the sensory neurons to the motor neurons. These connections are antagonistic, establishing the ocular position as a point of equilibrium. Despite a rotation of the head, the gaze remains stable.
In this thesis, we propose applying a neural control structure based on an antagonistic method. For vehicular control, the equilibrium point in the tire-road contact dynamics is set at the optimal slip. The response is therefore modulated in such a way that if the slip threshold is exceeded, the torque level is reduced and vice versa. This antagonistic behavior allows learning to be performed during normal operation without the risk of the system becoming unstable.
To replicate this type of neural structure, as well as the learning algorithms found in biological systems, it is necessary to define the neuron model used. This model must replicate biological behavior with a low computational cost to facilitate its integration in embedded systems in vehicles.
The most widely used neural network model is called Artificial Neural Network (ANN). However, this approach does not encode the signal in the same way as the procedure that takes place in biological systems. Biological mechanisms of learning are based on the synchronization of firing between contiguous neurons. In the case of ANNs, there is no firing in the neuron, but an activation function that does not take time into account. Consequently, ANNs do not reproduce biological learning faithfully.
In order to take advantage of these learning strategies, the next generation of neural networks encodes the information with a time evolution using electrical impulses. This characteristic gives rise to the so-called Spiking Neural Network (SNN).
The well-known SNN model proposed by Izhikevich stands out for its good biological representation and low computational cost. In this model, two differential equations reproduce the membrane potential and recovery based on rat neurons.
Since SNN uses impulses to encode information, it is necessary to translate the input and output signals to interact with the environment. A biological system uses sensory and motor neurons for this transformation. Sensory neurons are

responsible for incorporating information from the environment into the nervous system. These neurons are responsible for translating external stimuli such as light in the optical receptors or accelerations in the semicircular channels.
Similarly, the information used in vehicular control, such as the slip or its optimal value, will be provided to the proposed controller and identification networks based on SNN. Biological systems not only encode information temporally but also spatially. Every variable encoded in spikes is distributed among a certain number of sensory neurons. Hence, by means of a series of Gaussian bells, the firing level of each neuron is determined. On the other hand, motor neurons are responsible for decoding the impulses in order to perform the desired action. As the information is encoded temporally and spatially, each motor neuron is associated with an increasing level of activity. Heinemann's size principle reproduces this behavior. For example, in muscles, each motor unit is associated with a type of muscle fiber that exerts a different force with a different fatigue resistance.
In addition to modeling the neuronal cell body, it is also necessary to model the connections between neurons, known as synapses. They provide the capacity to establish complex relationships between inputs and outputs. In a biological synapse, the arrival of an impulse leads to the release of neurotransmitters that are responsible for opening the channels that allow the circulation of current in the postsynaptic neuron, giving rise to a new impulse. If this connection is direct, causing a firing in the postsynaptic neuron, the connection is considered electrical. On the other hand, if a high concentration of neurotransmitters is necessary to open several receptor channels, the connection is considered chemical. In this thesis, a synapse model based on the opening and closing of channels to model both kinds of behavior is proposed. This way, channels are opened as new electrical impulses are received and the opening time is determined as a function of the conductance.
Both the neuronal and synapse models allow the reproduction of the biological learning mechanisms by using the temporal difference between presynaptic and postsynaptic neuron impulses. This learning reproduces the neuronal plasticity through which the synaptic strength is modified. The learning mechanism used in this thesis is the so-called Spike Time-Dependent Plasticity (STDP). By means of an STDP rule, the plasticity of the synapse is modified in such a way that neurons that fire synchronously are the most affected by the learning process. As Donald Hebb summarizes, ‘neurons that fire together, wire together’. To establish how much each of them should be modified, it is necessary to model the release of dopamine, which is responsible, together with STDP, for the training of the neural network. To perform supervised learning, in which the error made is known continuously, dopamine is modeled directly

according to this error. In motor learning, the error is defined as the difference between the target and current value.

This work proposes a control algorithm based on a structure inspired by reflex arcs. The number of neuronal connections as well as whether they are inhibitory or excitatory are optimized to increase the robustness of the algorithm. However, the synaptic strengths will be adapted to each operating condition. This way, the proposed STDP algorithm adjusts each synapse to minimize the error made at every moment.

It should also be noted that in the design process of a control system, it is necessary to carry out simulations and testing to evaluate the performance of the proposed algorithm. In this work, the algorithm will be simulated and tested on different adherence conditions to verify its robustness and performance prior to its integration in a real vehicle.

The main limitation to accomplish this goal is the computational capacity of the real-time embedded systems used for vehicle control. In consequence, the size of the network as well as its update frequency are the main constraints when performing simulations.

The models and control algorithms have been programmed using MATLAB and SIMULINK. These software programs allow the direct compilation of the code as well as its execution in real-time, which is mostly used in the automotive industry hardware (DSPACE).

The combination of the aforementioned software and hardware make fast data collection and algorithm modifications possible during the experimentation phase. The implementation of the neural network in an FPGA or neuromorphic hardware accelerates the execution of the neural model, allowing the use of larger and more complex nets. This increasing speed is due to the hardware implementation of the neural model using an application-specific integrated circuit (ASIC) rather than the execution of the model on a universal processor. However, the experimental stage in vehicular systems represents a key phase in the development of the algorithm, hence the implementation of the algorithm in a real vehicle will be more relevant than the size of the network.

It should also be noted that, to simulate scenarios where the level of longitudinal adherence in the tire-road contact is controlled, braking is prioritized over stability or traction. This is due to the difficulty of replicating the simulations in an experimental environment since stability and traction tests might compromise safety with the research vehicles available.

Simulations have been carried out for both two and four-wheeled vehicles. For this purpose, BIKESIM and CARSIM were used in the initial development and simulation stages, where the behavior of the vehicle, suspension system and tires were obtained.These programs are intended to study vehicle behavior on tracks and they provide a good representation of a vehicle's movements thanks to the use of complex vehicle models. However, using them for the sole purpose of performing longitudinal emergency braking is not justified, since its computational cost is high. For this reason, a planar three Degree-of-Freedom (DOF) models have been developed in this thesis with a low computational cost that allows the parallel training of a large number of simulations, accelerating the development of the controller.

The degrees of freedom chosen for two-wheeled vehicles are longitudinal, vertical and pitch. This model is called the bicycle model since it does not take into account the lateral dynamics as it has no effect on the longitudinal control strategy developed. In four-wheeled vehicles, the vertical influence is reduced due to the height of the center of gravity and the vehicle's dimensions. However, a yaw movement can occur in the vehicle as the longitudinal forces of each tire may have lateral offset. Therefore, in this case, the three degrees of freedom used are longitudinal, lateral, and yaw.

The proposed algorithm has been compared to other control strategies. Thus, during the development of the thesis, classical algorithms based on sliding and wheel angular acceleration thresholds as well as optimized fuzzy logic-based algorithms have been simulated. A benchmark has thus been established for a subsequent evaluation of the proposed neural algorithm. Key Performance Indicators (KPIs) have been used to make this comparison, evaluating quantitatively the response of the controller to different contact conditions.

To perform this comparison, a series of braking tests according to regulation 13 (E/ECE/- TRANS/505/Rev.1/Add.12/Rev.8. 3. Regulation No. 13) have been reproduced. In this regulation, tests have been performed on different surfaces at various speeds. Furthermore, the performance of the brake system has also been tested in varying adhesion conditions. These tests have made it possible to analyze controller stability, which is difficult to demonstrate in algorithms based on neural networks.

Finally, as pointed out on several occasions, experimentation is a key phase to validate the correct functioning of the algorithm. To this end, a exchange period at the Swedish University of Kungliga Tekniska Högskolan (KTH) in Stockholm was carried out. The stay with a duration of 3 months, from April 1 to June 30 2021, was funded by the Ministry of Universities (EST19/00075). During the stay, it was possible to perform real tests with the electric Research Concept Vehicle (RCVe) of the receiving group. This vehicle is equipped with a brake-by-wire system that allows continuous regulation of the braking pressure. The vehicle is controlled by DSPACE hardware, which facilitates direct code compilation from SIMULINK. The main problem encountered was the low computational capacity which limited the test to only two wheels. To evaluate the performance of the algorithm under different adhesion conditions, tests were conducted at the Arlanda test track. The tests were carried out starting from 6 m/s, a speed limited by the vehicle design, with emergency braking to a stop. The tested conditions were high and low adhesion along with all possible transitions, i.e., low adhesion surface to high adhesion surface and vice versa as well as asymmetric braking, where the left wheel remained on the low grip surface while the right wheel was in high grip.

As mentioned before, at the beginning of this summary, this doctoral thesis is a compilation of four papers. Each paper has been devoted to describing a proposed solution to the problems encountered in the development of this work. All in all, this process has contributed to achieving the final objective of developing a control scheme based on biological networks successfully. Next, the papers that compose this thesis are described.

The first paper, entitled ‘Bio-inspired spiking neural network for nonlinear systems control’ was published in the journal Neural Networks in 2018. It establishes the basis of the neural control algorithm developed during the thesis. The neuronal structures proposed in this work are reflex arcs that react instantaneously to the appearance of a stimulus. These neuronal connections present low complexity with few connections. This results in a controller where the action is direct, which causes high-frequency oscillations in the tracking of the target signal. In addition, a reduced number of neurons have been used, which also implies high noise due to decoding. Despite these limitations, found during the realization of this work, the algorithm demonstrated its ability to control nonlinear systems. Two examples of applications were implemented: a DC motor and a muscle model control. The method used in this first paper to obtain the synaptic strengths was a genetic algorithm, using random initialization to obtain the optimal result. This learning method has to be performed off-line and implies that, during the simulation, unstable control conditions may occur.

Since this previous work lacked continuous learning, as well as that it was not applied to a real vehicle system, the methodology was further developed in order to achieve the objectives of the thesis. For this reason, further advances were described in a second paper that aimed to learn concerning the problems that arise when implementing control algorithms in a real vehicle. To this end, the limitations of embedded hardware were studied and a Traction Control System (TCS) was developed. This article was published in the Sensors journal in 2019 with the title: Low-Cost FPGA-Based Electronic Control Unit for Vehicle Control Systems. This work described the control scheme used as well as identifying the limitations of each component more profoundly.

Required times for the measurement and pre-processing of the velocity signals obtained by means of a magnetic encoder were verified. This limitation has been taken into account in the simulations subsequently carried out. The importance of a correct model of the actuator has been emphasized to ensure that the mathematical model used reproduces the measured behavior properly. Tests carried out on a test bench made it possible to define the motor response to a torque setpoint. This allowed adjusting the algorithm based on fuzzy logic to keep the slip level stable. One of the main disadvantages of this embedded hardware is the difficulty of implementing the code developed in MATLAB. Therefore, for the following implementations, a real-time operating system was employed using the code generated by the MATLAB compiler.

Once the control scheme was defined, a third paper focused on the development of a control algorithm able to cope with variable adhesion conditions. The use of fuzzy logic was proposed, based on previous work carried out by the research group. To grant the fuzzy logic controller the ability to adapt to different road types, it was necessary to train the algorithm for all possible levels of adhesion. The possible transitions between adhesion levels were taken into account. Since this task involved a huge number of iterations, it was decided to use an optimization mechanism based on coevolution. The optimization efforts focused on those surfaces where the worst results were obtained. This third paper was published in 2021 in IEEE Transactions on Vehicular Technology with the title: Co-evolutionary Optimization of a Fuzzy Logic Controller for Antilock Braking Systems under Changing Road Conditions. This work was also supported by real experimentation with a two-wheeled vehicle. The complexity of the correlation between experimentation and simulation was highlighted.

The use of estimators based on the Extended Kalman Filter (EKF) has demonstrated its ability to determine the forces in the tire-road contact. Initially, this estimation strategy was selected to be implemented in the algorithm developed in this thesis. Nevertheless, it has been found that the use of the EKF to identify the types of road has two main drawbacks. One is the need for a tire model capable of representing the variations in grip. This may require the tire to be modelled using a test bench, which is costly and does not allow the user of the vehicle to replace the tire with another brand or model. Another associated problem is the delay experienced during transients. In these cases, estimated values provided by the EKF algorithm will not be sufficiently accurate, making it more suitable to resort to more complex algorithms, such as the Unscented Kalman Filter (UKF) or other types of classifiers. In consequence, it was proposed to integrate the identification of the road type with the biological control network by means of an offline trained classification structure.

Therefore, further development of the biologically-based neural networks to perform control tasks as well as the required neural connections and the learning mechanism used had to be faced. In order to facilitate learning to optimize its behavior under previously inexperienced conditions, a control algorithm capable of learning in a real vehicle during its normal operation was developed. To this end, the biological behavior to perform control tasks and the necessary neural connections as well as the learning mechanism used was investigated. This led to a neural learning algorithm published in the journal Neurocomputing in 2021 with the title: A biological-like controller using improved spiking neural networks. In this paper, a mathematical muscle model was used to reproduce the motion of a single joint. By means of a structure inspired by reflex arcs, response times similar to those experienced by the neural control of a human being were obtained. In addition to the proposed neural network, a learning mechanism based on neuroplasticity was implemented. This allows identifying situations in which learning is required through supervised learning. To correct the fault, dopamine is released, which is responsible for modulating STDP learning according to the error made. With this approach, it is possible to learn from a suboptimal response or after a change in the dynamics.

Besides, a new synapse model based on the opening of multiple channels was proposed in this paper. These are used to model neurotransmitter release by the presynaptic neuron, as well as the input current of the postsynaptic neuron. Thus, less distortion is introduced into the information processed by the network, and a faster response is obtained. In addition, this neuron model can be used for decoding processes by translating impulses into a control action. The latter has a major impact when the network is intended for control. This same structure has been used for the vehicular control proposed in this thesis, as previously mentioned. The only modification required is to define the new input and output variables. This means changing from having the current and target position in the previous applications as input to using the current slip and its optimum value in vehicular control. As output, a torque is applied to the wheel instead of muscular stimulation.

Finally, a fifth paper is currently being written. In this last paper, which is also described in the thesis body, the neural structure developed for the braking control scheme proposed has been implemented. It integrates the identification of parameters, the neural network for the detection of adhesion conditions and the control neural network. The whole system was improved during the previously mentioned stay in Sweden and it was implemented in the electric Research Concept Vehicle (RCVe). After verifying the correct operation of the algorithm in a real vehicle and its ability to adapt to different adhesion conditions, the work that was initially considered, has been concluded in this thesis.

The developed controller has been compared with the state of the art in an objective way, demonstrating its superiority over algorithms that do not have the ability to adapt to changing conditions. In addition, the bio-inspired controller has a very simple structure that can be applied to other engineering problems, opening up very attractive new lines of research.

Keywords

Spiking Neural Network (SNN), Vehicle Control, Wheel Slip Control (WSC), Supervised Learning, Spike Time-Dependent Plasticity (STDP).

Resumen

En esta tesis se propone un nuevo algoritmo de control basado en redes neuronales biológicas para maximizar las fuerzas longitudinales en el contacto neumático-carretera en situaciones de emergencia de conducción con vehículos terrestres. Esta tesis ha sido financiada por el Ministerio de Universidades a través de la beca de Formación de Profesorado Universitario (FPU17/03161) concedida al autor en 2018. La tesis ha tenido una duración total de 3 años. En la memoria inicial entregada al Ministerio se preveía una duración de 4 años, destinando el último año a la redacción y conclusiones de la tesis. Sin embargo, se ha podido realizar todo el trabajo en tres años.

La tesis se presenta en forma de compendio de publicaciones. Se presentan cuatro trabajos publicados en revistas de alto impacto que apoyan la investigación, describiendo la metodología necesaria para la implementación de un controlador bioinspirado en un sistema vehicular. Además, se obtendrá la Mención Internacional de Doctorado ya que se ha realizado una estancia de tres meses en un grupo de investigación de una universidad extranjera por parte del doctorando.

Además, el autor de esta tesis ha participado como colaborador en los siguientes proyectos de investigación, relacionados con el tema de la tesis:

- "Determinación en tiempo real de las características del contacto neumático-carretera mediante algoritmos bioinspirados para la mejora de la seguridad activa en vehículos " (TRA2015-67920-R). Durante los dos años previos a la inscripción en el programa de doctorado se establecieron las bases de la tesis. En este periodo se puso de manifiesto la relevancia del algoritmo de control en una emergencia.
- "Sistema de frenado regenerativo basado en algoritmos bioinspirados" (UMA18-FEDERJA-109). Iniciado durante la ejecución de la beca FPU y que continúa en la actualidad.
- "Métodos de identificación del tipo de carretera basados en redes neuronales para vehículos eléctricos" (PID2019-105572RB-I00). Iniciado durante la ejecución de la subvención FPU y continúa en la actualidad.

Esta tesis estaba vinculada a los objetivos de estos proyectos de investigación ya que se centraban en la mejora de la eficiencia y la seguridad de los vehículos recurriendo a algoritmos avanzados de control y estimación. En este sentido, se desarrollaron algoritmos bioinspirados y redes neuronales para abordar los retos de estos proyectos. El control del vehículo es también un factor clave en estos proyectos donde se estudia el comportamiento entre el neumático y el

asfalto. Esta tesis se centra en el control longitudinal del vehículo, donde gestionando el par aplicado a la rueda, ya sea por frenado o tracción, se maximiza la fuerza obtenida en el contacto.

Una vez establecido el punto de partida y el contexto de la tesis, se describen a continuación los principales problemas para desarrollar una metodología de control óptimo. En primer lugar, hay que destacar la gran importancia de estimar las fuerzas en el contacto neumático-carretera con un alto grado de precisión, ya que de ellas depende la estabilidad del vehículo. Estas fuerzas de contacto muestran un claro comportamiento no lineal. Además, también existen variaciones debidas al entorno en el que se conduce el vehículo. Por otro lado, la principal variable relacionada con el nivel de adherencia que experimenta un neumático al rodar sobre una superficie es el deslizamiento, que puede definirse como la diferencia de velocidad entre la rueda y el vehículo. Por lo tanto, es necesario conocer la velocidad del vehículo para obtener el deslizamiento. Sin embargo, la velocidad del vehículo es un parámetro que sigue siendo difícil de medir en los vehículos actuales. Además, los modelos de neumáticos también se ven afectados por otros parámetros que influyen en su respuesta, como la temperatura, el desgaste, la presión de los neumáticos, etc. Por tanto, desarrollar un controlador capaz de gestionar todos los datos y variables del contacto neumático-carretera es una tarea compleja que requiere de algoritmos que puedan hacer frente a todos los posibles escenarios de conducción con un coste computacional razonable. Como solución a este problema, en este trabajo se propone un algoritmo de control capaz de adaptarse a condiciones inesperadas de forma dinámica. Para lograr este objetivo, como en otros problemas de ingeniería, la respuesta está en la naturaleza. Así, el algoritmo de control desarrollado se basa en el sistema nervioso de los seres vivos en forma de una estructura de control bioinspirada capaz de aprender durante su funcionamiento normal.

La descripción del esquema global utilizado es necesaria para entender los requisitos para el desarrollo de un algoritmo de control longitudinal del vehículo. El controlador tiene que adaptarse a la adherencia actual entre el neumático y la carretera y tiene que proporcionar las acciones de control necesarias para maximizar las fuerzas longitudinales evitando así el bloqueo de las ruedas. Los principales componentes de dicho esquema de control son:

Modelo	Vehículo Contacto neumático-calzada Actuadores.
Algoritmo	Estimación de parámetros Identificación de las condiciones de adherencia. Controlador
Mediciones	Medición de parámetros

Por lo tanto, los siguientes requisitos deberían incorporarse a cada uno de estos componentes para cumplir la tarea requerida:

-Vehículo: Transferencia de carga y grados de libertad.
-Contacto neumático-carretera: Fricción no lineal.
-Actuadores: Respuesta temporal.
-Medición de parámetros: Resolución y retrasos.
-Estimación de parámetros: Dinámica del vehículo y retrasos.
-Identificación de las condiciones de adherencia: Datos necesarios.
-Controlador: Respuesta rápida y capacidad de adaptación.

El modelo del vehículo debe tener en cuenta la transferencia de carga que se produce al acelerar y frenar, así como tener un número suficiente de grados de libertad para reproducir adecuadamente los principales movimientos del vehículo. En cuanto al modelo de neumático, debe ser una función no lineal del deslizamiento para reproducir adecuadamente la fricción neumático-carretera. Además, también debe incluirse su respuesta transitoria, ya que debe considerarse el retraso en la aparición de las fuerzas de fricción. Para ello, se utiliza la longitud de relajación para modelar la respuesta transitoria. El modelo utilizado también debe tener en cuenta la influencia de las condiciones ambientales, como la temperatura, la presión, la humedad, la carretera....
En cuanto a la medición y la estimación de parámetros, es crucial considerar los retrasos introducidos por los sensores, así como su resolución. Por ejemplo, los encoders utilizados para medir la velocidad angular de las ruedas tienen un número reducido de pulsos por revolución, lo que a bajas velocidades puede provocar problemas para detectar el bloqueo de las ruedas.
Asimismo, el valor de deslizamiento es necesario para estimar las condiciones de adherencia. Para obtener el valor de deslizamiento, hay que determinar la velocidad de las ruedas y la velocidad de la carrocería del vehículo. Esta última

no puede medirse directamente con los sensores del vehículo a un coste razonable. Además, otras tecnologías para la medición de la velocidad, como las basadas en el Sistema de Posicionamiento Global (GPS), no pueden utilizarse en este caso debido al retraso en su medición. Por ello, la velocidad del vehículo se obtiene combinando algoritmos de fusión y estimación de datos. Esto se suele resolver utilizando algoritmos basados en el filtro de Kalman y midiendo variables del sistema como las aceleraciones captadas por la Unidad de Medición Inercial (IMU). Esta tarea se realiza teniendo en cuenta la dinámica del vehículo de forma que se puedan definir las variables de estado.

Una vez obtenida la velocidad longitudinal del vehículo y el deslizamiento, es de vital importancia la identificación del tipo de carretera por la que circula el vehículo. La detección del tipo de carretera es un tema de continuo estudio. Por el momento, aún no se ha propuesto una solución estandarizada. Hay dos formas principales de afrontar este reto. El primer enfoque para realizar esta tarea se basa en el conocimiento de la dinámica de los neumáticos. En este caso, el principal problema que hay que abordar es que el modelo de neumático utilizado debe ser capaz de caracterizar todas las condiciones de conducción posibles, incluida la influencia de todos los parámetros que afectan al neumático. Esto hace que la implementación de esta estrategia sea un reto debido a la cantidad de datos necesarios para construir el modelo y la complejidad del mismo asociada, lo que dificulta su implementación en aplicaciones en tiempo real.

El segundo método recurre a las redes neuronales para realizar la tarea de clasificación del tipo de carretera. Estas estructuras pueden replicar el modelo de neumático y establecer la relación entre el tipo de carretera y otras variables medidas en el vehículo, como las vibraciones o una cámara de vídeo que capture la carretera. La metodología propuesta en esta tesis se enmarca en este segundo enfoque. Así, la misma estructura de red neuronal utilizada para realizar tareas de control se utiliza para identificar el tipo de carretera.

A continuación, los actuadores se encargan de convertir la acción de control en fuerzas que modulan el deslizamiento de la rueda. En este sentido, el reto es conseguir un funcionamiento rápido y fiable, ya que el bloqueo de una rueda es un proceso que puede tener lugar en menos de 200 ms. El comportamiento global del sistema puede verse reducido si no se aborda adecuadamente el modelado de los actuadores. En el caso de diferentes modos de actuación, por ejemplo en vehículos eléctricos con fricción y frenado regenerativo, habrá que definir una estrategia óptima.

El último componente es el algoritmo de control, que se encarga de proporcionar la acción requerida en el vehículo. El algoritmo de control debe ser capaz de regular el par de la rueda para mantener el deslizamiento de la rueda cerca de su valor óptimo según las condiciones de contacto entre el neumático y la carretera. Para ello, debe ser capaz de reconocer y adaptarse a las diferentes condiciones de conducción haciendo uso del nivel de deslizamiento estimado y del valor de deslizamiento óptimo deseado. La actuación puede implicar la regulación de los pares aplicados a las ruedas mediante un actuador. Los controladores más utilizados se basan en el Control de Modo Deslizante (SMC), la lógica difusa y el Control Predictivo de Modelos (MPC). Esta tesis recurre a una red neuronal de base biológica que, a diferencia de los anteriores controladores, puede adaptarse a los cambios en la dinámica del contacto durante la ejecución del algoritmo. De este modo, si el vehículo se enfrenta a una condición de adherencia nunca antes experimentada, el algoritmo de control se adaptará mediante una estrategia de aprendizaje para maximizar las fuerzas longitudinales y, por tanto, evitar el bloqueo de las ruedas.

De todos los componentes que intervienen en el esquema de deslizamiento de las ruedas, el algoritmo de control es el que más influye en el comportamiento final. Por lo tanto, la mayor parte del esfuerzo de investigación debe centrarse en el desarrollo de un algoritmo óptimo. En este sentido, el ser humano ha demostrado tener una capacidad superior para controlar la dinámica del contacto neumático-carretera. Así, llevar un vehículo hasta los límites de adherencia de forma controlada y segura es el principal objetivo de cualquier competición automovilística. En este caso, el objetivo es maximizar el agarre, normalmente para reducir el tiempo necesario para cubrir una distancia fija, manteniendo la estabilidad del vehículo. La capacidad de los pilotos profesionales para adaptarse a un nuevo vehículo, así como la detección del límite de adherencia en condiciones cambiantes (nuevo compuesto de neumático, circuito, condiciones meteorológicas, etc.) es sorprendente.

Como se ha demostrado, el control óptimo de un sistema complejo en condiciones de funcionamiento cambiantes es una tarea difícil que requiere un funcionamiento adecuado de los diferentes componentes del algoritmo de control. Sin embargo, los seres vivos se enfrentan continuamente a estos problemas y los resuelven adecuadamente en la mayoría de los casos.

La estrategia desarrollada en esta tesis se basa en el estudio del control motor en sistemas biológicos. En primer lugar, se intenta comprender cómo las conexiones neuronales de un ser humano o animal determinan la respuesta a los estímulos externos y permiten corregir el error cometido. En el caso del contacto con los neumáticos, el ser humano es capaz de adaptar el porcentaje de aceleración o frenado en función de la vista, las aceleraciones experimentadas por los canales semicirculares, los sonidos, etc.

Sin embargo, el ser humano no conoce el nivel de deslizamiento en cada momento. Esta es la ventaja del control electrónico, ya que al disponer de esta información clave se pueden conseguir resultados similares a los de un ser humano entrenado utilizando una estructura de control más sencilla. Para ello, la definición de la estructura de control requiere modelar adecuadamente los sistemas biológicos.

El estudio del control biológico permite comprender cómo se establecen las conexiones neuronales. Existen dos teorías sobre los posibles esquemas de control en los sistemas biológicos. La primera recurre a un modelo interno del sistema a controlar. Esto implica un alto nivel de conocimiento de la dinámica del sistema, lo que limita la capacidad de aprendizaje debido a que el modelo interno debe ser modificado para adaptarse a las variaciones. La segunda teoría se basa en el control por umbral, mediante el cual, sin necesidad de un modelo interno, se establece un punto de equilibrio. Cuando se supera este umbral, se produce una acción de control. Así, modificando el punto de equilibrio, se puede controlar un sistema biológico. Las conexiones neuronales se modifican para mantener el equilibrio en el punto de trabajo. Mientras que la teoría del modelo interno implica una estructura de control compleja y difícil de descodificar, la teoría del control del umbral presenta una estructura sencilla que sólo requiere un circuito neuronal para mantener el equilibrio.

Esta última teoría, denominada Hipótesis del Punto de Equilibrio (EPH), es la que se aplica en esta tesis. Por lo tanto, a través del estudio de las estructuras biológicas en humanos y animales, se pretende encontrar aquellas que muestran un comportamiento similar al descrito por la EPH. A partir de los trabajos realizados por Kandel se obtuvo la estructura de control así como los mecanismos de aprendizaje implicados en los seres vivos. Para ello, utilizó Aplysia, un animal que tiene un tamaño de neuronas muy grande, lo que facilita su decodificación. Posteriormente, se han descodificado muchas otras estructuras animales. En los seres humanos, se han podido determinar algunas estructuras de control, por ejemplo, algunas asociadas a los reflejos, llamadas arcos reflejos. Aun así, la gran mayoría del cerebro y el sistema nervioso humanos siguen siendo desconocidos y representan un gran reto técnico debido al elevado número de neuronas y conexiones que componen una estructura tan intrincada.

A partir del estudio de los arcos reflejos, es posible establecer el comportamiento global de la red neuronal encargada del control. Por ejemplo, en el reflejo vestíbulo-ocular, el control continuo de la mirada se mantiene gracias a las aceleraciones medidas por los canales semicirculares. La estructura que se encarga del movimiento ocular establece las vías neuronales que van desde las neuronas sensoriales a las motoras. Estas conexiones son antagónicas, estableciendo la posición ocular como un punto de equilibrio. A pesar de la rotación de la cabeza, la mirada permanece estable.

En esta tesis, se propone aplicar una estructura de control neuronal basada en un método antagonista. Para el control vehicular, el punto de equilibrio en la dinámica de contacto neumático-carretera se fija en el deslizamiento óptimo.

Por lo tanto, la respuesta se modula de forma que si se supera el umbral de deslizamiento se reduce el nivel de par y viceversa. Este comportamiento antagónico permite el aprendizaje durante el funcionamiento normal sin el riesgo de que el sistema se vuelva inestable.
Para replicar este tipo de estructura neuronal, así como los algoritmos de aprendizaje encontrados en los sistemas biológicos, es necesario definir el modelo de neurona utilizado. Este modelo debe replicar el comportamiento biológico con un bajo coste computacional para facilitar su integración en los sistemas embebidos de los vehículos.
El modelo de red neuronal más utilizado es el denominado Red Neural Artificial (ANN), sin embargo, este enfoque no codifica la señal de la misma manera que tiene lugar en los sistemas biológicos. Los mecanismos biológicos de aprendizaje se basan en la sincronización de los disparos entre neuronas contiguas. En el caso de las ANN, no hay disparos en la neurona, sino una función de activación que no tiene en cuenta el tiempo. Por todo ello, las ANN no reproducen fielmente el aprendizaje biológico.
Para aprovechar estas estrategias de aprendizaje, la siguiente generación de redes neuronales codifica la información temporalmente mediante impulsos eléctricos. Esta característica da lugar a las denominadas Redes Neuronales de Impulsos (SNN).
El conocido modelo SNN propuesto por Izhikevich destaca por su buena representación biológica y su bajo coste computacional. En este modelo, dos ecuaciones diferenciales reproducen el potencial de membrana y la recuperación basada en neuronas de rata.
Dado que la SNN utiliza impulsos para codificar la información, es necesario traducir las señales de entrada y salida para interactuar con el entorno. Un sistema biológico utiliza neuronas sensoriales y motoras para esta transformación. Las neuronas sensoriales se encargan de incorporar la información del entorno al sistema nervioso. Estas neuronas se encargan de traducir los estímulos externos, como la luz en los receptores ópticos o las aceleraciones en los canales semicirculares.
De igual modo, la información utilizada en el control vehicular, como el deslizamiento o su valor óptimo, se transmitirá al controlador e identificación propuestos basados en SNN. Los sistemas biológicos no sólo codifican la información temporalmente, sino también espacialmente. Cada variable codificada en impulsos se distribuye entre un cierto número de neuronas sensoriales. Así, mediante una serie de campanas gaussianas, se determina el nivel de disparo de cada neurona. Por otro lado, las neuronas motoras se encargan de descodificar los impulsos para realizar la acción deseada. Como la información se codifica temporal y espacialmente, cada neurona motora se asocia a un nivel de actividad creciente. El principio de tamaño de Heinemann

reproduce este comportamiento. Por ejemplo, en los músculos, cada unidad motora está asociada a un tipo de fibra muscular que ejerce una fuerza diferente con una resistencia a la fatiga diferente.

Además de modelar el cuerpo celular neuronal, también es necesario modelar las conexiones entre neuronas, conocidas como sinapsis. Estas proporcionan la capacidad de establecer relaciones complejas entre las entradas y las salidas. En una sinapsis biológica, la llegada de un impulso provoca la liberación de neurotransmisores que se encargan de abrir los canales que permiten la circulación de la corriente en la neurona postsináptica, dando lugar a un nuevo impulso. Si esta conexión es directa, provocando un disparo en la neurona postsináptica, la conexión se considera eléctrica. En cambio, si es necesaria una alta concentración de neurotransmisores para abrir varios canales receptores, la conexión se considera química. En esta tesis se propone un modelo de sinapsis basado en la apertura y cierre de canales para modelar ambos comportamientos. Así, los canales se abren a medida que se reciben nuevos impulsos eléctricos y el tiempo de apertura se determina en función de la conductancia.

Tanto los modelos neuronales como los de sinapsis permiten reproducir los mecanismos de aprendizaje biológico utilizando la diferencia temporal entre los impulsos neuronales presinápticos y postsinápticos. Este aprendizaje reproduce la plasticidad neuronal mediante la cual se modifica la fuerza sináptica. El mecanismo de aprendizaje utilizado en esta tesis es la llamada Plasticidad Dependiente del Tiempo del Impulso (STDP). Mediante una regla STDP, la plasticidad de la sinapsis se modifica de modo que las neuronas que disparan sincrónicamente son las más afectadas por el proceso de aprendizaje. Como resume Donald Hebb, "las neuronas que se disparan juntas se conectan". Para establecer cuánto debe modificarse cada una de ellas, es necesario modelar la liberación de dopamina, responsable, junto con el STDP, del entrenamiento de la red neuronal. Para realizar un aprendizaje supervisado, en el que se conoce continuamente el error cometido, la dopamina se modela directamente en función de este error. En el aprendizaje motor, el error se define como la diferencia entre el valor objetivo y el actual.

Este trabajo propone un algoritmo de control basado en una estructura inspirada en los arcos reflejos. El número de conexiones neuronales, así como si son inhibitorias o excitatorias, se optimizan para aumentar la robustez del algoritmo. Sin embargo, las fuerzas sinápticas se adaptarán a cada condición de funcionamiento. De esta forma, el algoritmo STDP propuesto ajusta cada sinapsis para minimizar el error cometido en cada momento.

También hay que tener en cuenta que en el proceso de diseño de un sistema de control es necesario realizar simulaciones y pruebas para evaluar el comportamiento del algoritmo propuesto. En este trabajo, el algoritmo será

simulado y probado en diferentes condiciones de adherencia para verificar su robustez y rendimiento antes de su integración en un vehículo real.
La principal limitación para lograr este objetivo es la capacidad de cálculo de los sistemas embebidos en tiempo real utilizados para el control del vehículo. En consecuencia, el tamaño de la red, así como su frecuencia de actualización son las principales limitaciones a la hora de realizar las simulaciones.
Los modelos y algoritmos de control se han programado utilizando MATLAB y SIMULINK. Estos programas permiten la compilación directa del código así como su ejecución en tiempo real en el hardware más utilizado por la industria del automóvil (DSPACE).
La combinación de dicho software y hardware hace posible una rápida recogida de datos y la modificación del algoritmo durante la fase de experimentación. La implementación de la red neuronal en una FPGA o hardware neuromórfico acelera la ejecución del modelo neuronal, permitiendo el uso de redes más grandes y complejas. Este aumento de la velocidad se debe a la implementación por hardware del modelo neuronal mediante un circuito integrado de aplicación específica (ASIC) en lugar de la ejecución del modelo en un procesador universal.Sin embargo, la fase de experimentación en los sistemas vehiculares representa una fase clave en el desarrollo del algoritmo, por lo que la implementación del algoritmo en un vehículo real será más relevante que el tamaño de la red.
También hay que tener en cuenta que, para simular escenarios en los que se controla el nivel de adherencia longitudinal en el contacto neumático-carretera, se prioriza el frenado sobre la estabilidad o la tracción. Esto se debe a la dificultad de replicar las simulaciones en un entorno experimental, ya que las pruebas de estabilidad y tracción podrían comprometer la seguridad con los vehículos de investigación disponibles.
Las simulaciones se han realizado tanto para vehículos de dos como de cuatro ruedas. Para ello se han utilizado BIKESIM y CARSIM en las fases iniciales de desarrollo y simulación, donde se ha obtenido el comportamiento del vehículo, del sistema de suspensión y de los neumáticos.
Estos programas están destinados a estudiar el comportamiento de los vehículos en los circuitos y proporcionan una buena representación de los movimientos del vehículo gracias a la utilización de modelos complejos del mismo. Sin embargo, utilizarlos con el único fin de realizar una frenada de emergencia longitudinal no está justificado, ya que su coste computacional es elevado. Por ello, en esta tesis se ha desarrollado un modelo plano de tres Grados de Libertad (GDL) con un bajo coste computacional que permite el entrenamiento en paralelo de un gran número de simulaciones, acelerando el desarrollo del controlador. Los grados de libertad elegidos para los vehículos de dos ruedas son el longitudinal, el vertical y el de cabeceo. Este modelo se

denomina modelo de bicicleta ya que no tiene en cuenta la dinámica lateral al no tener efecto en la estrategia de control longitudinal desarrollada. En vehículos de cuatro ruedas, la influencia vertical se reduce debido a la altura del centro de gravedad y a las dimensiones del vehículo. Sin embargo, puede producirse un movimiento de guiñada en el vehículo, ya que las fuerzas longitudinales de cada neumático pueden tener un desplazamiento lateral. Por lo tanto, en este caso, los tres grados de libertad utilizados son longitudinal, lateral y de guiñada.

El algoritmo propuesto se ha comparado con otras estrategias de control. Así, durante el desarrollo de la tesis se han simulado algoritmos clásicos basados en umbrales de deslizamiento y de aceleración angular de la rueda, así como algoritmos optimizados basados en lógica difusa. Se establece así un punto de referencia para la posterior evaluación del algoritmo neuronal propuesto. Para realizar esta comparación se utilizan Indicadores de Rendimiento (KPIs) que evalúan cuantitativamente la respuesta del controlador a diferentes condiciones de contacto.

Para realizar esta comparación, se han reproducido una serie de ensayos de frenado según el reglamento 13 (E/ECE/- TRANS/505/Rev.1/Add.12/Rev.8. 3. Reglamento nº 13). En este reglamento, los ensayos se realizan en diferentes superficies a distintas velocidades. Además, también se comprueba el rendimiento del sistema de frenado en distintas condiciones de adherencia. Estas pruebas permiten analizar la estabilidad del controlador, que es difícil de demostrar en los algoritmos basados en redes neuronales

Por último, como se ha señalado en varias ocasiones, la experimentación es una fase clave para validar el correcto funcionamiento del algoritmo. Para ello, se ha realizado una estancia en la Universidad sueca de Kungliga Tekniska Högskolan (KTH) en Estocolmo. La estancia con una duración de 3 meses, del 1 de abril al 30 de junio de 2021, fue financiada por el Ministerio de Universidades (EST19/00075).

Durante la estancia se han podido realizar pruebas reales con el Research Concept Vehicle (RCVe) del grupo receptor. Este vehículo está equipado con un sistema de frenado "by-wire" que permite la regulación continua de la presión de frenado. El vehículo está controlado por el hardware DSPACE, que facilita la compilación directa del código desde SIMULINK. El principal problema que se ha encontrado es la baja capacidad de cálculo, que ha limitado la prueba a sólo dos ruedas. Para evaluar el rendimiento del algoritmo en diferentes condiciones de adherencia, se realizaron pruebas en la pista de pruebas de Arlanda. Las pruebas se realizaron a partir de 6 m/s, una velocidad limitada por el diseño del vehículo, con una frenada de emergencia hasta la parada. Las condiciones probadas son de alta y baja adherencia junto con todas las transiciones posibles, es decir, de superficie de baja adherencia a alta adherencia y viceversa, y frenado asimétrico, en el que la rueda izquierda permanece en la superficie de baja adherencia mientras que la derecha está en alta adherencia.

Como se ha mencionado al principio de este resumen, esta tesis doctoral es un compendio de cuatro artículos. Cada uno de ellos se ha dedicado a describir una solución propuesta a los problemas encontrados en el desarrollo de este trabajo. En definitiva, este proceso ha contribuido a conseguir el objetivo final de desarrollar un esquema de control basado en redes biológicas. A continuación se describen los trabajos que componen esta tesis.

El primer trabajo, titulado 'Bio-inspired spiking neural network for nonlinear systems control' fue publicado en la revista Neural Networks en 2018. En él se establecen las bases del algoritmo de control neuronal desarrollado durante la tesis. Las estructuras neuronales propuestas en este trabajo son arcos reflejos que reaccionan de forma instantánea ante la aparición de un estímulo. Estas conexiones neuronales presentan una baja complejidad con pocas conexiones. Esto da lugar a un controlador en el que la acción es directa, lo que provoca oscilaciones de alta frecuencia en el seguimiento de la señal objetivo. Además, se utiliza un número reducido de neuronas, lo que también implica un alto ruido debido a la decodificación. A pesar de estas limitaciones, encontradas durante la realización de este trabajo, el algoritmo demostró su capacidad para controlar sistemas no lineales. Se implementaron dos ejemplos de aplicaciones: un motor de corriente continua y el control de un modelo muscular. El método utilizado en este primer trabajo para obtener las fuerzas sinápticas fue un algoritmo genético, utilizando una inicialización aleatoria para obtener el resultado óptimo. Este método de aprendizaje tiene que realizarse fuera de línea e implica, que durante la simulación, pueden darse condiciones de control inestables.

Dado que este trabajo previo carecía de aprendizaje continuo, así como que no se aplicaba a un sistema vehicular real, se desarrolló más la metodología para lograr los objetivos de la tesis. Por ello, se describieron nuevos avances en un segundo trabajo que pretendía conocer los problemas que surgen al implementar algoritmos de control en un vehículo real. Para ello, se estudiaron las limitaciones del hardware embebido y se desarrolló un Sistema de Control de Tracción (TCS). Este artículo fue publicado en la revista Sensors en 2019 con el título: 'Low-Cost FPGA-Based Electronic Control Unit for Vehicle Control Systems'. En este trabajo se describió con mayor profundidad el esquema de control utilizado así como se identificaron las limitaciones de cada componente.

Se verificaron los tiempos necesarios para la medición y el preprocesamiento de las señales de velocidad obtenidas mediante un encoder magnético. Esta limitación se ha tenido en cuenta en las simulaciones realizadas posteriormente.

Se destaca la importancia de un correcto modelo del actuador para que el modelo matemático utilizado reproduzca adecuadamente el comportamiento medido. Los ensayos realizados en un banco de pruebas permitieron definir la respuesta del motor a una consigna de par. Esto permitió ajustar el algoritmo basado en la lógica difusa para mantener estable el nivel de deslizamiento. Uno de los principales inconvenientes de este hardware embebido es la dificultad de implementar el código desarrollado en MATLAB.

Por ello, para las siguientes implementaciones se empleará un sistema operativo de tiempo real utilizando el código generado por el compilador de MATLAB.

Una vez definido el esquema de control, el tercer trabajo se centró en el desarrollo de un algoritmo de control capaz de hacer frente a condiciones variables de adherencia. Se propuso el uso de la lógica difusa basándose en trabajos anteriores realizados por el grupo de investigación. Para otorgar al controlador de lógica difusa la capacidad de adaptarse a los diferentes tipos de carretera, fue necesario entrenar el algoritmo para todos los posibles niveles de adherencia. Se tuvieron en cuenta las posibles transiciones entre niveles de adherencia. Como esta tarea implicaba un gran número de iteraciones, se decidió utilizar un mecanismo de optimización basado en la coevolución. Los esfuerzos de optimización se centraron en aquellas superficies en las que se obtienen los peores resultados. Este tercer trabajo fue publicado en 2021 en IEEE Transactions on Vehicular Technology con el título: 'Coevolutionary Optimization of a Fuzzy Logic Controller for Antilock Braking Systems under Changing Road Conditions'. Este trabajo también se apoyó en la experimentación real con un vehículo de dos ruedas. Se destacó la complejidad de la correlación entre la experimentación y la simulación.

El uso de estimadores basados en el Filtro de Kalman Extendido (EKF) ha demostrado su capacidad para determinar las fuerzas en el contacto neumático-carretera. En consecuencia, inicialmente se seleccionó esta estrategia de estimación para implementarla en el algoritmo desarrollado en esta tesis. Sin embargo, se ha comprobado que el uso del EKF para identificar el tipo de carretera tiene dos inconvenientes principales. Uno es la necesidad de un modelo de neumático capaz de representar las variaciones de adherencia. Para ello es necesario modelar el neumático en un banco de pruebas, lo que resulta costoso y no permite al usuario del vehículo sustituir el neumático por otra marca o modelo. Otro problema asociado es el retraso experimentado durante los transitorios. En estos casos, los valores estimados proporcionados por el algoritmo EKF no serán lo suficientemente precisos, siendo más adecuado recurrir a algoritmos más complejos, como el Filtro de Kalman Unscented (UKF) u otros tipos de clasificadores. Se propuso, por tanto, integrar la identificación del tipo de carretera con la red de control biológico mediante una estructura de clasificación entrenada fuera de línea.

Para ello, es necesario desarrollar las redes neuronales basadas en la biología para realizar las tareas de control, así como las conexiones neuronales necesarias y el mecanismo de aprendizaje utilizado. Con el fin de facilitar el aprendizaje para optimizar su comportamiento en condiciones previamente no experimentadas, se desarrolló un algoritmo de control capaz de aprender en el vehículo real durante su funcionamiento normal. Para ello, se investigó el comportamiento biológico para realizar tareas de control y las conexiones neuronales necesarias, así como el mecanismo de aprendizaje utilizado. Esto condujo a un algoritmo de aprendizaje neuronal publicado en la revista Neurocomputing en 2021 con el título: 'A biological-like controller using improved spiking neural networks'. En este trabajo se utilizó un modelo matemático de músculo para reproducir el movimiento de una sola articulación. Mediante una estructura inspirada en los arcos reflejos, se obtuvieron tiempos de respuesta similares a los experimentados por el control neuronal de un ser humano. Además de la red neuronal propuesta, se implementó un mecanismo de aprendizaje basado en la neuroplasticidad. Esto permite identificar situaciones en las que es necesario aprender mediante un aprendizaje supervisado. Para corregir un defecto, se libera dopamina, que se encarga de modular el aprendizaje STDP en función del error cometido.Con este enfoque, es posible aprender a partir de una respuesta subóptima o tras un cambio en la dinámica.
Además, en este trabajo se propone un nuevo modelo de sinapsis basado en la apertura de múltiples canales. Estos se utilizan para modelar la liberación de neurotransmisores por parte de la neurona presináptica, así como la corriente de entrada de la neurona postsináptica. Así, se introduce menos distorsión en la información procesada por la red y se obtiene una respuesta más rápida. Además, este modelo de neurona puede utilizarse para los procesos de decodificación, traduciendo los impulsos en una acción de control. Esto último tiene un gran impacto cuando la red se destina al control. Esta misma estructura se utiliza para el control vehicular propuesto en esta tesis, como ya se ha mencionado. La única modificación necesaria es definir las nuevas variables de entrada y salida. Esto significa pasar de tener como entrada la posición actual y la posición objetivo en las aplicaciones anteriores a utilizar el deslizamiento actual y su valor óptimo en el control vehicular. Como salida, se aplica un par a la rueda en lugar de una estimulación muscular.
Por último, se está redactando un quinto trabajo. En este trabajo, que también se describe en el cuerpo de la tesis, se implementa la estructura neuronal desarrollada para el esquema de control de frenado propuesto. Integra la identificación de parámetros, la red neuronal para la detección de condiciones de adherencia y la red neuronal de control. Todo el sistema fue mejorado durante la estancia mencionada anteriormente y se implementó en el electric

Research Concept Vehicle (RCVe). Tras comprobar el correcto funcionamiento del algoritmo en el vehículo real y su capacidad de adaptación a diferentes condiciones de adherencia, se da por finalizado el trabajo que inicialmente se planteaba realizar en esta tesis.

El controlador desarrollado se ha comparado con el estado del arte de forma objetiva demostrando su superioridad sobre los algoritmos que no tienen la capacidad de adaptarse a las condiciones cambiantes. Además, el controlador bioinspirado tiene una estructura muy sencilla que puede aplicarse a otros problemas de ingeniería, abriendo nuevas líneas de investigación muy atractivas.

Palabras Claves
Spiking Neural Network (SNN), Control Vehicular, Wheel Slip Control (WSC), Aprendizaje Supervisado, Spike Time-Dependent Plasticity (STDP).

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Thank you!

Javier Pérez Fernández

Contents

Part I: Summary of performed work

1.Introduction

1.1.Background

Active safety systems in vehicles make it possible to avoid accidents or to reduce the severity of the consequences in the event of a crash through the intervention by means of different types of actuators on the vehicle. These systems ensure efficient and safe driving without loss of vehicle maneuverability , i.e. capable of being steered or directed. This thesis intends to develop active safety systems that can take advantage of the maximization of the tire longitudinal forces during braking and traction processes.
The most well-known commercial systems in this field are the Anti-lock Brake System (ABS) for braking and Traction Control System (TCS) for traction. The introduction of these systems significantly reduced the number of accidents and their severity since their implementation more than 40 years ago. Since then, the number of vehicles that include active safety systems in their standard configuration has increased progressively. In addition, regulations have also made some of these systems compulsory for new vehicles. This represents a constantly growing research line that is even more emphasized by the appearance of the first autonomous vehicles.

The first of these systems developed was the ABS. This system contributes to reducing the braking distance and to maintain the vehicle's maneuverability in emergency braking. It prevents a possible accident by minimizing the braking distance, thus avoiding accidents and collisions with other vehicles and road users. Achieving a good ABS performance was not possible until the dynamics of the contact between the road and tire was thoroughly studied and modelled. These studies demonstrated that by preventing the tire from locking, a greater grip and a reduced braking distance could be obtained, this way improving the maneuverability of the vehicle. The appearance of electronic control units and electro-hydraulic actuators made it possible to implement these systems in new vehicles. This way, the first commercial ABS was launched by Robert Bosch GmbH in 1978. At that moment, the cost and size of ABS modules were high. In the present day, however, the production cost and size of ABS modules is low. In addition, they incorporate new functionalities, such as ESP, TCS, …

Nowadays, statistics of vehicles that are equipped with ABS have demonstrated the effectiveness of these systems. As a result, the European Union decided to make it mandatory for all new four-wheeled vehicles in 2003.

Furthermore, in Europe, this requirement has recently been extended to two-wheeled vehicles in 2017. Motorcycles are a sector where the number of accidents is huge and the severity of injuries is extremely high. Making this system mandatory will contribute to minimizing the number of accidents and their consequences.

The efficiency and functionalities of these systems are in continuous evolution. The performance of a safety system is very much related to the optimization of the control of the forces in the tire-road contact area. This way, a full understanding of the dynamics of tire-road contact is a constant source of research and development. A clear example of this is considering the problems and scrutiny taking place in choosing a tire model in motor sport competitions.

Today, controlling the dynamics of tire-road contact becomes even more important with the emergence of autonomous vehicles. In this case, the goal is to minimize the number of human interventions during movement of the vehicle. Thus, the research and optimization of control technologies in active safety systems is still a challenge for the automotive industry and academic institutions. Thus, it is possible to define the priority research topics within these types of systems by analyzing the control architecture of a passenger vehicle (Figure 1).

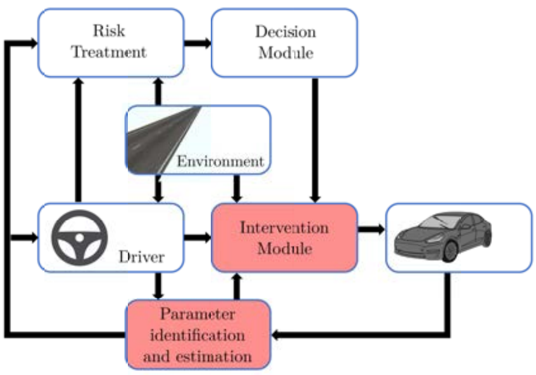


Figure 1. Vehicular control architecture (Modular description)

During an emergency, active safety systems can partially or completely take control of the vehicle to avoid an accident. Therefore, the identification and parameter estimation module, as well as the intervention module, are key during emergencies since they deal with vehicle inputs and outputs respectively.

On one hand, the identification and parameter estimation module obtains the necessary information to know the current vehicle states, including those related to contact between the tire and the road. On the other hand, the intervention module responds according to the programmed control logic to optimize the grip and maneuverability of the vehicle in each situation. This thesis proposes a novel approach for the implementation of both modules.

1.2. Problem statement

Both the parameter identification and estimation and the intervention modules still present different unsolved challenges. In the identification module, two problems stand out: an accurate determination of vehicle speed and a reliable detection of the type of road, i.e. the tire-road adherence. Similarly, the control algorithm of the intervention module has to deal with nonlinearities due to variable dynamics of the tires. A low integration cost, adequate real-time response, optimal performance, and robustness have to be ensured for the implementation of these modules in vehicle systems.

Parameter identification and estimation	Vehicle speed Road detection
Intervention	Variable road-tire dynamics Embedded (Low-cost, Real-time) Robust control (Stability)

Firstly, regarding vehicle speed measurement, each available technology has limitations. For example, the Global Positioning System (GPS) technology provides a feasible solution for autonomous vehicle driving. Its latency makes it inappropriate for emergencies, though. On the contrary, the CORREVIT optical device is a low latency system but its cost is excessively high for massive implementation in standard vehicles. Currently, the most widely used low-cost method resorts to standard sensors already installed in vehicles and estimation algorithms to obtain an approximation of real vehicle speed.

Secondly, a robust road detection that can cope with changes in adhesion conditions is of vital importance to safety control systems. However, road type detection also has challenges to tackle. The tire-road contact has high variability due to weather conditions (rain, snow, ice, humidity, pressure ...), thermal factors (temperature of the tires and their sidewalls), and, macro-texture and micro-texture factors, among others. Either Cause-based or Effect-based algorithms can be used to detect the road condition.

All of the above show the variability and uncertainty that are transmitted to the intervention module from the parameter identification and estimation modules. The control algorithm running on the vehicle has to deal with this variability and adapt accordingly to the changes experienced when facing new working conditions. In addition, there are at least three additional requirements that vehicle control algorithms have to fulfill. First, a low computational cost, since the final algorithm has to run in real-time on a limited capacity embedded system for mass production.

Second, it has to be capable of controlling nonlinearities present in the tire-road contact. Last, the controller has to be robust, i.e. it has to guarantee the stability of the system during its operation and in the presence of any possible perturbations. These requirements complicate the adaptability of control algorithms. Furthermore, vehicle stability has to be ensured even during the learning phase. Usually, the way to overcome this problem is to train the algorithm offline and, when the performance obtained in simulations is satisfactory, implement it in the vehicle afterwards. The algorithm is consequently not tuned during its execution in real operating conditions, which limits its ability to adapt to new circumstances that have not been previously studied.

1.3. Purpose of the study

This thesis aims to solve each of the problems mentioned in the previous section but focusing mainly on improving the adaptability of the control algorithm to conditions not previously experienced.

Regarding the parameter identification module, the most feasible solution is adopted within the existing ones. This way, an algorithm based on an Extended Kalman Filter (EKF) to estimate vehicle speed has been developed. This algorithm resorts to the wheel angular velocity and vehicle angular acceleration to obtain a robust speed estimation. Wheel angular velocity is obtained from the encoders installed in all vehicles equipped with an ABS, in the form of a toothed or magnetic wheel with a sensor whose frequency output is proportional to the angular velocity. Acceleration measurement requires the use of an Inertial Measurement Unit (IMU). Inertial units are increasingly being installed in vehicles thanks to the reduction in the cost of Micro-ElectroMechanical Systems (MEMS). This way, this approach makes use of the sensors commonly installed in vehicles.

The proposed road detection methodology also makes use of the previously mentioned sensors. In addition, it also resorts to the measurement provided by the brake pressure sensors. This sensor is currently found in most vehicles, at least in the master cylinder. With all this information and knowing the dynamics of the tire-asphalt contact, the forces experienced by the tire can be estimated. To do so, an EKF-based algorithm and a classifier have been developed to obtain the optimum grip level. The main disadvantage of this method is poor accuracy when the longitudinal acceleration is low since the forces experienced are small. In any case, for emergency braking or traction procedures, the controller tries to maximize the deceleration or acceleration respectively, longitudinal forces being high in both cases.

Finally, a new approach for the intervention module based on a bio-inspired neural network is proposed. Thus, the system is endowed with learning capabilities thanks to the reproduction of neural plasticity found in biological systems.

Artificial neural networks (ANNs) were among the first structures that mimicked the behavior of biological neural networks. These artificial networks have been widely used in classification and clustering applications. Their application in control, although less widespread, is also effective. Artificial neural networks (ANNs) provide the opportunity to replicate neural structures to understand and reproduce their behavior and performance. ANNs are based on the use of activation functions to model firing. However, these ANNs are simplified models that do not accurately reproduce the behavior of biological neural systems since they do not take into account time as occurs in nature. On the contrary, SNNs resort to time-sensitive activation functions that lead to firing in the neuron, being much closer to the real ones. This makes it possible to replicate biological electrical impulses as well as time synchronization mechanisms that open the door to learning mechanisms that cannot be applied in ANNs.

To this end, Spiking Neural Networks (SNN) capable of modeling the electrical signals employed by biological neurons with a low computational cost have been developed. The proposed neural networks are able to modify their behavior by adjusting the neural connections, called synapses, without losing control of the vehicle. Furthermore, a supervised learning algorithm has been developed. In this algorithm, the synchronization between neurons through Spike Time-Dependent Plasticity (STDP) modifies synapse strength. To ensure the robustness of the controller, a neural structure based on reflex arcs of biological control mechanisms is used. Synapse changes can be made during the execution of the algorithm, which allows online learning in the vehicle during normal operation.

1.4. Literature review

Research based on vehicle dynamics and control is constantly evolving. Universities and research centers dedicate a lot of time and effort to publishing articles and books in vehicle-related fields. Unfortunately, the main source of research and development is found within the private vehicle manufacturing industry, as its investment capacity is much higher compared to public research groups. Consequently, little information is publicly available on active safety systems of vehicles on the road. Nevertheless, literature on vehicle safety systems is extensive. A literature review is summarized below according to the module in which the papers are classified.

1.4.1. Parameter identification and classification module

1.4.1.1. Longitudinal speed determination

Regarding the calculation of vehicle speed, studies can be classified according to the way they perform the estimation, i.e. direct or indirect measurement of speed. GPS is often used for direct measurement, but studies such as Supej et al. (2014) have shown that latency limits its functionality. For indirect measurement, vehicle dynamics measurements such as accelerations and angular velocities of the wheels are used. Thus, Alcazar et al. (2021) described a more accurate measurement system based on sensors available in the majority of electric vehicles. Certainly, for indirect speed calculation, EKF is the most widely used estimator (Joševski et al. (2017)); works such as Guo et al. (2013) implemented this algorithm in an FPGA, thus validating its application in embedded systems. The use of observers (Chen et al. (2018), Wang et al. (2009)) and data fusion (Ding et al. (2020)) are also commonly used.

1.4.1.2. Road identification

The tire-road contact dynamics is determined by the tire model, so it requires information about the type of road the tire is in contact with.The road type detection in real-time is still a challenge to be solved due to the great number of internal and external agents present in the road-tire contact point (i.e. wear, weather conditions, maintenance, presence of contaminants, ...). Therefore, there are several methodologies to tackle this problem. The most effective method falls into the 'effect-based' category. As presented by Rajamani et al. (2010), detection occurs when the forces experienced by the tire are high. Taylor et al. (2010) proposed a double Kalman structure. Castillo et al. (2015) described a hybrid EKF and ANN structure to estimate road adherence. Other proposals are based on an Unscented Kalman Filter (UKF) or moving horizon estimation, as in Zhang et al. (2019). Accelerometers (Singh et al. (2013) , Andrades et al. (2020)) or wheel speed sensors (Umeno et al. (2002)) are commonly used for this identification method.
Despite being effective algorithms, their performance degrades when low forces are acting on the wheels, so they are not appropriate to warn safety systems prior to an emergency. On the contrary, the 'cause-based' category makes use of cameras (Casselgren et al. (2007)) or radars (Viikari et al. (2009)), which allows anticipating an emergency. These methods are perfectly compatible and can be combined with 'effect-based' methods.

1.4.1.3. Tire model

The modeling of tire contact with the road, as previously mentioned, is the main factor that defines the dynamics of a vehicle. For this reason, research focused on this factor is very extensive and complex. Some approaches use physical models to modulate their behavior, such as the LuGre (Canudas-de-Wit et al. (2003)) or Brush model (Clover et al. (1998), Van Zanten et al. (1989)). However, empirical models, such as Burckhardt (1993)'s, are generally preferred. Pacejka (2012)'s empirical model established the basis of what is currently one of the most widely used tire models in the industry, the MF-tire. This acronym stands for Magic Formula, as he called the equation that fits the experimental data.

Modifications to this formula have been made to include the influence of other parameters, such as speed in Cabrera et al. (2010). In deed, the evolution of the MF-Tire into a dynamic model called MF-Swift is commonly used by vehicle manufacturers. However, unlike its predecessor, there is very little information about it since it is currently owned by the private company Siemens. This model uses real data, as in Cabrera et al. (2018), to determine the parameters of the MF. Subsequently, it fits the tire dynamic behavior by means of real testing, such as Acosta et al. (2020). Hence, the MF-Swift model provides the grip level, taking into account the road profile. For this reason, it is one of the most advanced models although its closed nature requires the payment of a license fee for its use.

Although most studies are focused on four-wheeled vehicles, there are also research papers on two-wheeled vehicles, providing experimental data such as those by Sharp et al. (2004) or simulations performed by Alcazar et al. (2020).

1.4.2. Intervention module

1.4.2.1. Wheel slip control (WSC)

Active safety systems that maximize longitudinal forces during braking and acceleration are generally based on slip control. This is due to the fact that tire dynamics are mainly determined by the difference between vehicle speed and the theoretically calculated forward speed based on wheel angular speed, as discussed above. Thus, this type of controller utilizes a target slip level based on the type of road. Next, the control algorithm is in charge of managing the wheel torque to maintain the wheel slip as close as possible to the target, either by using friction brakes, a combustion engine, an electric motor, or a combination of them.

Pretagostini et al. (2020) summarized the main WSC algorithms from those based on a threshold, (Day et al. (2018)) and (Kogut et al. (2017)) such as the first one developed by Bosch (Reif (2014)), to Model Predictive Control (MPC). Pretagostini et al. (2020) also showed that each control strategy has its advantages and disadvantages, without a clear superiority of one over the other. Thus, algorithms based on well-known industrial controllers, such as

PID, are still proposed by several authors such as Sharkawy et al. (2010) and Li et al. (2016). Fuzzy logic-based controllers are part of the most developed controllers in literature, either alone (Mauer (1995)) or in a hybrid structure or with other controllers (Li et al. (2012)), or with self-organization (Lin et al. (2013)) . Similarly, proposals based on sliding surface control (SMC) (Shim et al. (2008)) and neural networks (Poursamad (2009)) are also frequently used in vehicular systems.
The appearance of electric vehicles has led numerous authors to adapt their algorithms to this new technology, as it has been summarized by Ivanov et al. (2015) and De Castro et al. (2013). This way, Khatun et al. (2003) used fuzzy logic to perform ABS and TCS control in an electric vehicle. Castillo et al. (2017) expanded these controller capabilities to allow them to regenerate energy. Independent electric motors also offer other control techniques, not available with previous technologies, such as torque vectoring (Goggia et al. (2015)),which maximizes the longitudinal forces for each wheel in traction and braking.
Although in fewer cases, the adaptation of WSC to two-wheeled vehicles is also studied, applying the same control logic, as in Cabrera et al. (2015) where a fuzzy-based torque regulation was used for traction control.

1.4.2.2. Bio-inspired control

Bio-inspired control is the main contribution of this thesis. This way, control schemes and structures found in real biological systems, which is the foundation of this work, are presented below.
Two control schemes are proposed: the first one is based on an internal model suggested by Kawato (1999) while the second one is based on a threshold control, which was presented by Feldman (2007). The main difference between both approaches is that the former requires the use of an internal model of the system, this model being unnecessary for the second one. This latter approach describes the basis of the Equilibrium Point Hypothesis (EPH) (Latash (2010)) and (Kistemaker et al. (2007)) which establishes how synergy between motor units (Latash (2011)) allows carrying out complex movements. Although supporters of the internal model theory, such as Wolpert et al. (1998) and Gomi et al., have tried to demonstrate deficiencies in EPH, it has been shown that this approach provides results (Kistemaker et al. (2020)) comparable to those obtained in real biological systems. Therefore, this control theory, which was further extended by Feldman (2015), for the referent control of action and perception is used in this thesis.
Regarding biological structures, Kandel (2015) was one of the precursors of the study of the control mechanisms of the Aplysia. This research has been extended to other animals such as the movement of the lamprey, which was

studied by Lansner et al. (1994). Undoubtedly, control structures involved in reflexes are of greater interest because they are capable of performing continuous control. One of the most studied reflex arcs is the Vestibulo-Ocular Reflex (VOR) (Haggerty et al. (2018)). This reflex controls eye movement as a response to the position and velocity of the head to stabilize sight. The structure of the VOR in humans (Ito (1998)) and (Branoner et al. (2016)) controls the eye using the semicircular canals to stabilize eye movement while maintaining equilibrium, as predicted in EPH.

1.4.2.3. Spiking neural network (SNN)

The modeling of the components of the nervous system is required to develop bio-inspired controllers. In particular, the main component of the nervous system is a cell called neuron. This cell is responsible for processing and transferring information within the nervous system. The first bio-inspired neural networks developed were called Artificial Neural Networks (ANN). However, these networks do not encode the information with impulses, the way this occurs in biological systems. In addition, they cannot emulate the learning mechanisms. On the contrary, Spiking Neural Networks (SNN) is a newer approach that emulates electrical impulses on the nervous system. Within this approach, there are models with different levels of computational complexity and biological representation, yet the model proposed by Izhikevich (2003) is one of the most widely used since it provides very good representation with low computational cost. This proposal has been boosted thanks to the appearance of the Hodgkin-Huxley (1952) model, which has allowed them to be used for the development of deep neural networks. Pfeiffer et al. (2018) describe the opportunities that this evolution represents. Other authors such as (Demin et al. (2018)) focus on the use of Recurrent Neural Networks (RNNs). However, studies are mainly applied to pattern recognition problems (Awadalla et al. (2012)), not existing many examples of its use in control applications (Bing et al. (2020)), (Wang et al. (2014)).

In addition to the neuronal model, information transmitted within the system is encoded by means of a sequence of impulses. Thus, it is necessary to develop a methodology to encode and decode this information. For encoding, an artificial spike train can be used directly or even a neuron itself, as a pulse generator. The latter is similar to sensory neurons that fire more or less depending on the external excitation. Normally, this type of coding is associated with modulation by Gaussian bells (Bohte et al. (2002)), (Oniz et al. (2015)) to distribute the information among several neurons.

On the other hand, decoding transforms spikes into a continuous variable, just as the motor units of muscles convert neuronal excitation into a force.

Kaiser et al. (2016) proposed the use of a muscle model to filter the impulses by using two of them in an antagonistic structure. If several neurons need to be decoded, they are distributed among different motor units using Henneman (1957)'s size principle.
Different simulation tools can be used to implement SNN algorithms with programming environments such as MATLAB and Python. Some project examples can be found in Brain (Goodman et al. (2008)) and Nengo (DeWolf et al. (2020)), where the network is enabled to run on polymorphic hardware such as Intel's Loihi. Furthermore, Izhikevich et al. (2007) modeled the complete brain with SNN and simulated it with C programming language, using a cluster.

1.4.2.4. Learning process

One of the main unknowns in biological neural systems is the mechanism of learning. Kandel (2015)'s study of Aplysia described the fundamental mechanisms of biological learning, thanks to which he was awarded the Nobel Prize. Doya et al. (2001) described the types of learning and classified them into supervised, unsupervised, and reinforced learning.
Examples of learning applied to SNN are described in SNN (Taherkhani et al. (2020))(Lobo et al. (2020))(Wang et al. (2020)). In addition, there are adaptations of reinforced learning (Izhikevich (2007)) and supervised learning (Taherkhani et al. (2018)). Both are mainly based on neural plasticity as a function of activity (Wei et al. (2019)), utilizing the STDP method, supervised learning applied using STDP being the most widely used. Dopamine modulation is also introduced to combine STDP learning with the reward in reinforced learning. This way, dopamine activates and deactivates STDP depending on the evolution of the learning process. Another factor to take into account is the initialization of the network, since an early determined structure (Arena et al. (2009)) may influence learning capacity and allows predicting the behavior of the network. The latter allows online learning without the risk of unpredictable responses as occurs with randomly initialized structures.
Finally, all the flexibility that SNN and learning algorithms allow to obtain new solutions, like modeling a biological system such as an arm by Spiiler et al. (2015), robot control (Wang et al. (2019)), (Tang et al. (2018)), (Bing et al. (2019)) or pattern recognition (Hao et al. (2020)).

1.5. Outline of the thesis

This thesis is organized into two parts: the first part introduces the work carried out during the first three years of the thesis. The second part includes papers published during this period as a first author.

The first part is structured as follows: the vehicle model including the road tire interaction as well as the actuators involved are described in Section 2.1. Next, the Wheel Slip Control (WSC) scheme used is defined (Section 2.2). The estimation needed is performed by using an Extended Kalman Filter (EKF), which is presented in Section 2.3. SNNs-based algorithms have been used to develop the rest of the components required for the WSC (identification and intervention), which are described in Section 2.4. Simulations and results are included in Section 3. Finally, the main conclusions of this research and future work are presented in Sections 4 and 5 respectively.

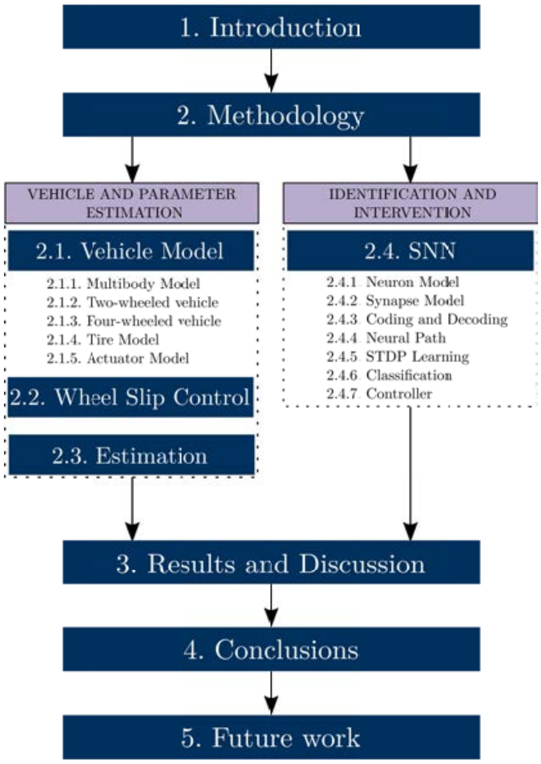


Figure 2. Thesis overall structure

The second part presents the articles that combines two research lines: vehicle dynamics and spiking neural networks. Thus, the published papers focus on solving challenges in both lines of research. Subsequently, a final paper has been written that merges the achievements so far to propose a complete vehicle safety system controlled with bio-inspired algorithms. Furthermore, results obtained in experimental tests have also been included in this final paper.

The first publication [1], prior to the beginning of the thesis, established the basis and gave insights into the viability of the proposal. This paper describes a neural control inspired by neural connections found in biological systems. The controller is capable of managing a nonlinear system with a complexity similar to the dynamics of a tire. However, no self-learning method was used.

With the second paper [2] published, the goal was to define a control scheme for tire contact dynamics, describing a model of the system and actuators. This paper allowed understanding the requirements that such a controller should have in terms of temporal response and low computational cost but also regarding the need to adapt to the environment. It has to be noted that several factors influence the dynamics of a tire. Taking all these aspects into account increases the complexity of designing the controller and limits it to a very specific use in a particular tire and vehicle. A simple controller capable of learning can be a more appropriate solution than a very complex and inflexible algorithm with many parameters to be tuned.

The third article [3] sought to explore the concept of adaptability using fuzzy logic. Fuzzy logic-based controllers are considered one of the most efficient control algorithms due to their low computational cost. By means of evolutionary learning, based on coevolution, the proposed controller was trained to obtain good behavior on different types of roads, as well as with sudden changes in the surface. The possible combinations between road types and changes are high so, by means of coevolution, the learning was focused only on those areas where the controller made the greatest error. This reduced the number of possible simulations and ultimately resulted in a controller capable of maximizing adhesion for all surfaces. The main problem that arose was what happened if the controller encountered a new surface, degradation, pressure, temperature, and other conditions. If so, it would be necessary to repeat the learning procedure from the beginning, which represented a great disadvantage for real-time applications. This way, in order to train the controller, it was necessary to simulate a large number of combinations, which required a large computational cost and prevented the algorithm from being updated in the final hardware.

Finally, in the fourth paper [4], the controller proposed in the first paper has been greatly improved by developing a neural model with a more advanced structure, the main contribution being the proposal of an STDP learning algorithm capable of learning during its normal operation. To this end, it has been applied to control a nonlinear model of an arm, being able to adapt to variations and perturbations in the system with responses similar to those experienced in the human body. Thus, an algorithm with a low computational cost, capable of learning in real-time, is proposed, which allows its application in embedded systems such as those used in vehicle control. All in all, this represents one of the main contributions of this thesis, not only being able to control a nonlinear system but also endowing the controller with the ability to adapt to possible changes in system dynamics.

In addition, all the knowledge acquired has been implemented in an experimental vehicle through a collaboration with the Swedish University of

KTH. During a three-month stay, the control algorithm based on neural networks was tested on a four-wheeled electric experimental vehicle (Research Concept Vehicle – RCVe) equipped with industry-recognized DSPACE controller hardware. These tests served to validate the proposed approach on a real vehicle. Figure 3 shows the overview of the thesis in a flow chart over time.

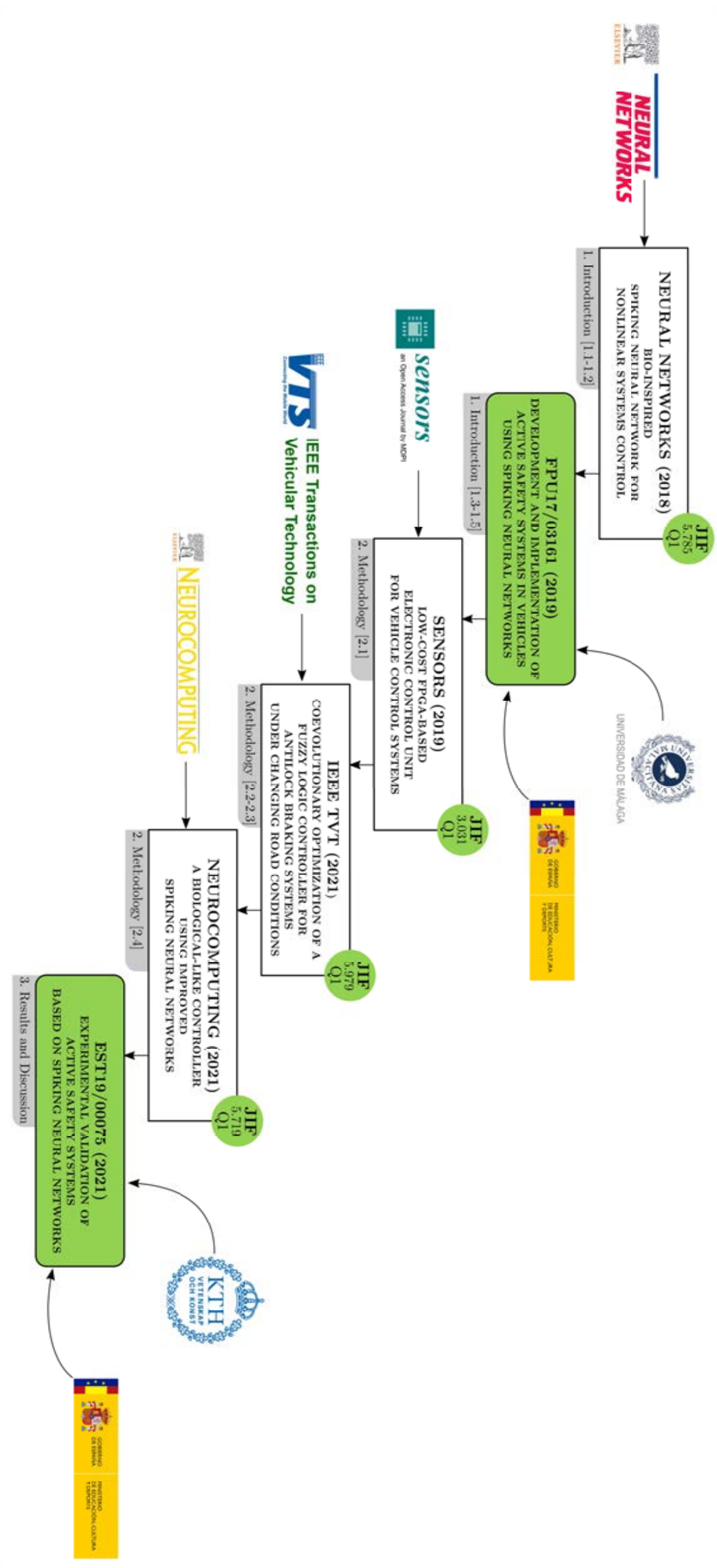


Figure 3. Thesis overview (Articles and grants linked to thesis sections)

Appended Papers

[1] Pérez Fernández, J., Cabrera, J. A., Castillo, J. J. & Velasco, J. M. Bio-inspired spiking neural network for nonlinear systems control. Neural Networks, 104, 15–25 (2018). DOI: 10.1016/j.neunet.2018.04.002

[2] Pérez Fernández, J., Alcázar Vargas, M., Velasco García, J. M., Cabrera Carrillo, J. A. & Castillo Aguilar, J. J. Low-Cost FPGA-Based Electronic Control Unit for Vehicle Control Systems. Sensors (Basel), 19, (2019). DOI: 10.3390/s19081834

[3] Pérez Fernández, J., Vargas, M. A., Garcia, J. M. V., Carrillo, J. A. C. & Aguilar, J. J. C. Coevolutionary Optimization of a Fuzzy Logic Controller for Antilock Braking Systems under Changing Road Conditions. IEEE Trans. Veh. Technol, 70, 1255–1268 (2021). DOI: 10.1109/TVT.2021.3055142

[4] Pérez Fernández, J., Vargas, M. A., Garcia, J. M. V., Carrillo, J. A. C. & Aguilar, J. J. C. A biological-like controller using improved spiking neural networks. Neurocomputing, (2021). DOI: 10.1016/j.neucom.2021.08.005

Related Papers

Aguilar, J. J. C., Pérez, J., García, J. M. V. & Carrillo, J. A. C. Regenerative intelligent brake control for electric motorcycles. Energies 10, (2017).

Cabrera, J. A., Castillo, J. J, Perez, J., García, J. M. V. & Hern, P. A Procedure for Determining Tire-Road Friction Characteristics Using a Modification of the Magic Formula Based on Experimental Results. Sensors (2018).

Alcazar, M., Perez, J., Mata, J. E., Cabrera, J. A. & Castillo, J. J. Motorcycle final drive geometry optimization on uneven roads. Mech. Mach. Theory 144, 103647 (2020).

Acosta, E. C., Aguilar, J. J. C., Carrillo, J. A. C., García, J. M. V., Perez, J., & Alcazar, M. Modeling of Tire Vertical Behavior Using a Test Bench. IEEE Access 106531–106541 (2020).

Alcazar, M., Perez, J., Velasco, J. M. & Carrillo, J. A. C. A Novel Method for Determining Angular Speed and Acceleration Using Sin-Cos Encoders. Sensors (2021).

Conferences

"Influence of tire dynamics on a braking process with ABS", XIV Congreso de Ingeniería del Transporte (CIT), Burgos, Spain, 2021

"Influence of temperature and speed on the dynamics of tire-road contact", Congreso Iberoamericano de Ingeniería Mecánica, CIBIM, Cartagena de Indias, Colombia, 2019.

"Influence of system dynamics in brake blending strategies for electric vehicles", 26th IAVSD Symposium on Dynamics of Vehicles on Roads and Tracks, IAVSD, Gothenburg, Sweden, 2019.

"A Traction Control System based on Co-evolutionary Learning in Spiking Neural Network (SNN)", 14th International Symposium on Advanced Vehicle Control (AVEC), IAVSD, Beijin, China, 2018.

"Regenerative control for an electric motorcycle", XIII Congreso Ibero-Americano de Ingeniería Mecánica, CIBIM, Lisbon, Portugal, 2017.

Press

"El sistema de seguridad vial más «inteligente»", La Razón, 2018. https://www.larazon.es/tecnologia/el-sistema-de-seguridad-vial-mas-inteligente-HJ18554715

"Investigadores de la UMA crean un sistema de seguridad inteligente para vehículos inspirado en la comunicación neuronal", EuropaPress, 2018. https://www.europapress.es/andalucia/malaga-00356/noticia-investigadores-uma-crean-sistema-seguridad-inteligente-vehiculos-inspirado-comunicacion-neuronal-20180529160034.html

"Desarrollan un sistema de seguridad inteligente inspirado en la comunicación neuronal", MálagaHoy, 2018. http://m.malagahoy.es/motor/Desarrollan-seguridad-inteligente-inspirado-comunicacion_0_1249675788.html

"Las neuronas inspiran la seguridad de los vehículos del futuro", Fundación Descubre. 2018. https://idescubre.fundaciondescubre.es/noticias/desarrollan-sistema-seguridad-inteligente-vehiculos-inspirado-la-comunicacion-neuronal/

TV interview

"Innovaciones para la seguridad del vehículo", Canal Sur enRed, 2018. https://www.canalsur.es/television/programas/enred/detalle/320.html?video=1406206&sec=

2.Methodology

This chapter is devoted to outlining the methodology followed to model a vehicle and the structure required to control it. Therefore, this chapter is divided into four sections focused on describing the vehicle model, the control scheme, the estimation, and the neural algorithms respectively. First, the vehicle model is described.

2.1.Vehicle Model

A vehicle model is required to replicate the behavior of the vehicle equipped with the Wheel Slip Control (WSC) proposed in this work.dui The use of an adequate vehicle model is crucial since it determines the dynamics of the system to be controlled. Therefore, it is important to set the minimum requirements of the model to achieve a good balance between computational cost and accuracy. For the study of longitudinal dynamics, the tire model is prioritized over the vehicle body model since the tire-road contact model is highly non-linear. The body model is mainly in charge of determining the vertical forces and velocities of each wheel, so the minimum requirement is that it has to be capable of providing a good representation of the load transfers associated with longitudinal acceleration.

2.1.1. Multibody Model

The use of a multibody model allows the calculation of speeds and forces considering all the degrees of freedom available in a vehicle. However, since this thesis mainly focuses on the control of longitudinal tire forces, the use of a multibody type model is not necessary. Nevertheless, two and four-wheel models developed by BikeSim and CarSim have been used. This allows validating the performance of the simpler models proposed below, as well as validating the developed control algorithm.

The main drawback of multibody models is the associated high computational cost, which limits the number of iterations to train the control algorithm. When developing new learning methodologies, it is necessary to test different configurations and types of control structures, thus fast simulation processes are desired, provided they represent the system correctly. Hence, the models used for the development of the proposed algorithms are presented below.

These models satisfy the low computational cost target by reducing the number of degrees of freedom and focusing on the longitudinal dynamics of the vehicle.

2.1.2. Two-wheeled vehicle

In this case, the planar model commonly known as a bicycle model, where only longitudinal and vertical forces appear, is used (Figure 4). This model can include the behavior of the damping system to correctly simulate the vertical load transfer during transients. Due to the risk involved in performing tests on two-wheeled vehicles at high speed, the tests were performed at low speed to avoid the possibility of rollover. This results in minimal impact on the suspension system during a test.

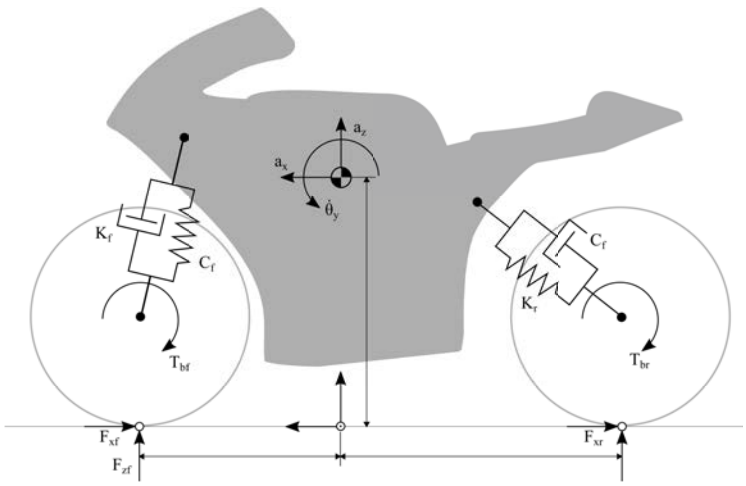


Figure 4. Planar motorcycle model

The governing equations used are those associated with 3 Degrees Of Freedom (3DOF) horizontal (1), vertical (2), and pitch (3).

$$M(\ddot{x}+\dot{\theta}\dot{z})=F_{xr}+F_{xf}+F_d \tag{1}$$
$$M(\ddot{z}+\dot{\theta}\dot{x}+g)=F_{zr}+F_{zf} \tag{2}$$
$$I_{yy}\ddot{\theta}=-F_{zf}L_f+F_{zr}L_r-F_{xf}z-F_{xr}z \tag{3}$$

Where x, y and z are with respect to Earth-fixed axes. In addition, the equations linked to the rotation of the front (4) and rear (5) wheels are also taken into account.

$$I_{wf}\dot{\Omega}_f=T_f-F_{xf}R_f \tag{4}$$
$$I_{wr}\dot{\Omega}_r=T_r-F_{xr}R_r \tag{5}$$

The parameters used in the model are summarized in the following Table 1:

Table 1. Motorcycle model parameters

Symbol	Description	Symbol	Description
x	Longitudinal displacement (COG)	C_f	Stiffness of front suspension
z	Vertical displacement (COG)	C_r	Stiffness of rear suspension
M	Mass	K_f	Front damping
θ	Pitch angle	K_r	Rear damping
Ω_f	Front wheel speed	F_d	Force drag
Ω_r	Rear wheel speed	T_f	External torque front tire
R_f	Front tire radius	T_r	External torque rear tire
R_r	Rear tire radius	F_{xf}	Front longitudinal force
L_f	Front half length	F_{xr}	Rear longitudinal force
L_r	Rear half length	F_{zf}	Front vertical force
I_{yy}	Inertia on the Y axis	F_{zr}	Rear vertical force
I_{wf}	Front wheel spin inertia		
I_{wr}	Rear wheel spin inertia		

2.1.3. Four-wheeled vehicle

A three Degree-Of-Freedom (DOF) model is used to reproduce the dynamics of a four-wheeled vehicle. This model takes into account longitudinal and lateral translation, as well as the yaw of the vehicle (Figure 5). However, this model does not consider vertical movement. Thus, it will be necessary to calculate the load transfer on each of the wheels by means of additional equations.

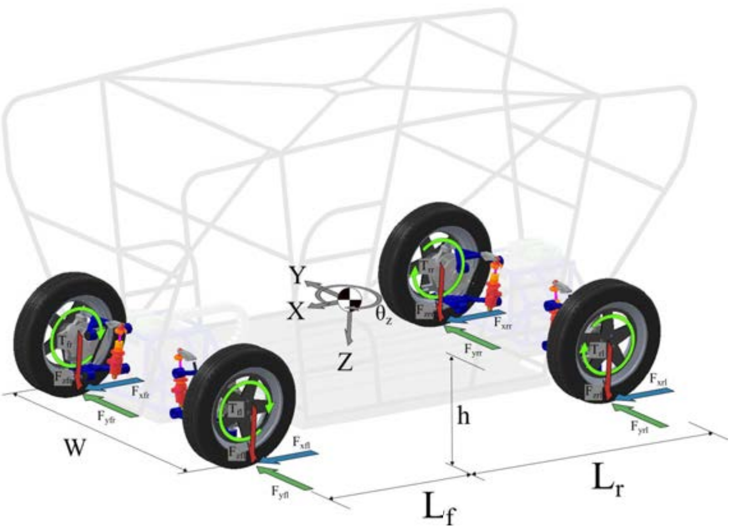


Figure 5. Four-wheel vehicle model

These model equations are similar to those of the two-wheeled vehicle model. However, in this case, lateral movement is more important than the vertical one. In this case, the equation for longitudinal forces (6), lateral forces (7), and yaw (8) are taken into account.

$$M(\ddot{x}-\dot{y}\,\dot{\theta})=F_{xfl}+F_{xfr}+F_{xrl}+F_{xrr}+F_{dx} \tag{6}$$
$$M(\ddot{y}+\dot{x}\,\dot{\theta})=F_{yfl}+F_{yfr}+F_{yrl}+F_{yrr}+F_{dy} \tag{7}$$
$$I_{zz}\dot{\theta}=L_f\left(F_{yfl}+F_{yfr}\right)-L_r\left(F_{yrl}+F_{yrr}\right)+0.5w(F_{xfl}-F_{xfr}+F_{xrl}-F_{xrr})+M_{dz} \tag{8}$$

Since pitch is not taken into account in this model, it is assumed that the vehicle always keeps the wheels in contact with the road. This assumption can be made based on the geometry, mass, and position of the Center Of Gravity (COG) in four-wheeled vehicles, which ensure the contact of the wheels with the road in almost all driving conditions. Therefore, the vertical load equations are presented for the front (9) and rear (10) axles with these assumptions. Similarly, the following equations are used to obtain the load on each wheel: front left (11) and right (12) as well as rear left (13) and right (14).

$$F_{zf}(L_f+L_r)=L_rMg-(\ddot{x}-\dot{y}\dot{\theta})Mh+hF_{dx}-M_{dy} \tag{9}$$
$$F_{zr}(L_f+L_r)=L_fMg-(\ddot{x}-\dot{y}\dot{\theta})Mh+hF_{dx}+M_{dy} \tag{10}$$
$$F_{zfl}=F_{zf}+(Mh(\ddot{y}+\dot{x}\,\dot{\theta})+hF_{dy}-M_{dx})\,\frac{2}{w} \tag{11}$$
$$F_{zfr}=F_{zf}-F_{xfl} \tag{12}$$
$$F_{zrl}=F_{zr}+(Mh(\ddot{y}+\dot{x}\,\dot{\theta})+hF_{dy}-M_{dx})\,\frac{2}{w} \tag{13}$$
$$F_{zrr}=F_{zr}-F_{xrl} \tag{14}$$

Additionally, each wheel has an associated rotational equation as in (4)(5) which has been omitted as they do not add further information.
The parameters used in the model are summarized in the following Table 2:

Table 2. Four-wheel vehicle model parameters

Symbol	Description	Symbol	Description
x	Longitudinal displacement (COG)	$F_{xf}= F_{xfl} + F_{xfr}$	Front longitudinal force
y	Lateral displacement (COG)	$F_{xr}= F_{xrl} + F_{xrr}$	Rear longitudinal force
M	Mass	$F_{yf}= F_{yfl} + F_{yfr}$	Front lateral force
θ	Yaw angle	$F_{yr}= F_{yrl} + F_{yrr}$	Rear lateral force
L_f	Front half length	$F_{zf}= F_{zfl} + F_{zfr}$	Front vertical force
L_r	Rear half length	$F_{zr}= F_{zrl} + F_{zrr}$	Rear vertical force
w	Vehicle width	F_d	Force drag
h	Height (COG)	M_d	Moment drag
I_{zz}	Inertia on the Z axis		

2.1.4. Tire Model

As previously emphasized, the tire model mainly determines the dynamics of the system to be controlled. Hence, it is of vital importance that the tire model should represent tire nonlinearity and transient response faithfully. In this case, the main problem encountered is the difficulty to obtain real tire data and to gain access to the more recent and advanced tire models due to industry secrecy. In this work, Pacejka's Magic Formula has been used. This model has been chosen because it can reproduce tire-road adhesion with a reduced number of parameters. In addition, it can be used to model possible variations in adhesion and transient response by adding a transient term.

In Pacejka's model, the longitudinal force equation (F_{xi}) is a function of the vertical force (F_{zi}) and a set of experimentally obtained parameters according to equation (15). These parameters $\{D_x, C_x, B_x, E_x\}$ define the behavior of the tire (16) on different surfaces as a function (P) of the type of road ($\lambda_{\mu xi}$) and the vertical dimensionless load by using equation (17) in combination with the nominal load (F_{z0}) of the tire.

$$F_{xi}=D_x \sin[C_x \arctan\{B_x\kappa_i-E_x(B_x\kappa_i-\arctan(B_x\kappa_i))\}] \tag{15}$$

$$\begin{cases} D_x=F_{zi}P_{D_x}(df_{zi},\lambda_{\mu xi}) \\ C_x=P_{C_x}(df_{zi}) \\ B_x=P_{B_x}(df_{zi},\lambda_{\mu xi}) \\ E_x=P_{E_x}(df_{zi}) \end{cases} \tag{16}$$

$$df_{zi}=\frac{F_{zi}-F_{z0}}{F_{z0}} \tag{17}$$

To model the transient response, the relaxation length (σ_x) is used, which provides the time response of the slip (κ_i) as a function of the longitudinal velocity (18).

$$\sigma_x \frac{d\kappa_i}{dt}+|\dot{x}|\kappa_i=R\Omega_i-\dot{x} \tag{18}$$

Since the study focuses on longitudinal forces, the used lateral model is considered purely linear since the experienced slip angle (α_i) will be reduced. Lateral forces are defined as a function of the cornering stiffness (C_y), the vertical load (F_{zi}), the road type ($\lambda_{\mu xi}$), and the slip angle (α_i) according to (19).To model the latter, equation (20) is used, which uses the lateral relaxation length (σ_y). Thus, it reproduce the transients as long as the slip angle variation is reduced, as in the case of longitudinal braking and traction tests.

$$F_{yi}=-C_y\alpha_i\lambda_{\mu xi}F_{zi} \tag{19}$$

$$\sigma_y \frac{d\alpha_i}{dt}+|\dot{x}|\alpha_i=-\dot{y} \tag{20}$$

2.1.5. Actuator Model

Just as the road-tire contact determines the dynamics of the system to be controlled, it is also necessary to take into account how the system will interact with it. A suitable model of the actuator used to impose forces on the tire is crucial to develop a control algorithm. A faster actuator allows less complex logic to be used since it is not necessary to anticipate the forces generated in the tire, while a slower actuator requires an algorithm capable of predicting its response. A common mistake made when developing control algorithms is not taking into account the time response of the actuators. This results in systems and controllers capable of maintaining the slip without any oscillation in simulations. However, this behavior is not realistic since system delays and temporal responses have a big influence on the overall performance of the controller. This fact can typically be observed when testing controllers only with simulations and not testing them in real systems. To avoid this issue, the controllers proposed in this thesis will be evaluated by means of experimental results obtained from research vehicles.

2.2. Wheel Slip Control (WSC)

The main contribution of this thesis is the development of a vehicle safety system based on the use of Spiking Neural Networks (SNN). To this end, a wheel slip control algorithm composed of three main modules, namely estimation, identification and intervention, has been proposed. This way, an EKF-based algorithm has been used to estimate the parameters required by the identification and intervention modules. Next, SNNs have been utilized to create the last two modules of the controller. All these modules are described in the following sub-sections. To control tire dynamics, it is necessary to achieve a particular slip level. This is due to the fact that tire dynamics are mainly determined by the slip level (κ). Furthermore, maximum longitudinal forces are obtained when an optimum slip level (κ_{opt}) for which the grip level is maximum is reached. In addition, the optimum slip level sets an inflection point where the dynamics change from being stable to becoming unstable. Hence, the controller should consider this optimum level to provide improved performance (Figure 6).

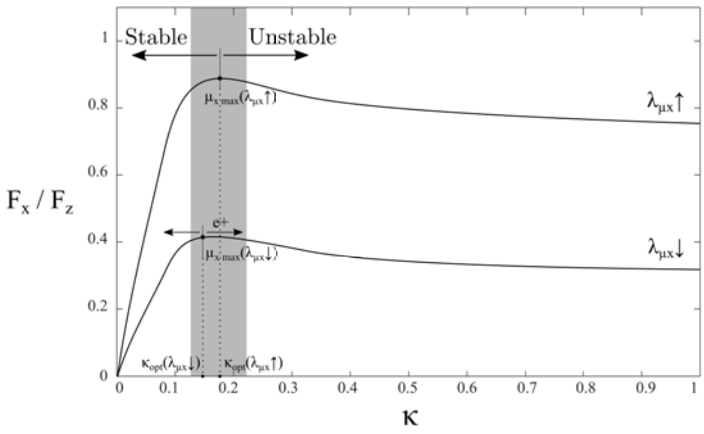


Figure 6. Stable and unstable tire region (Slip vs longitudinal grip)

Unfortunately, the slip and its optimum value cannot be measured directly. Consequently, it is necessary to estimate them based on variables measured by sensors installed in the vehicle. For the optimal slip, it is also necessary to use a classifier since it depends on the type of road. Thus, it will be necessary to develop a detection mechanism.

The controller that controls the slip and its optimum value must be able to regulate the torque applied to the wheels. To this end, slip error is commonly used, which is defined as the optimal slip subtracted from the actual slip. However, it is also possible to use the integral or derivative of the error as well as to establish more complex relationships between both variables.

In this thesis, using an estimator based on an Extended Kalman Filter (EKF) for indirect determination of the slip is proposed. Besides, Spiking Neural Networks (SNN) that integrate classifier and control functions are developed. Figure 7 shows how the components (Estimator, Classifier, and Controller) of the WSC are connected to obtain the proposed control scheme.

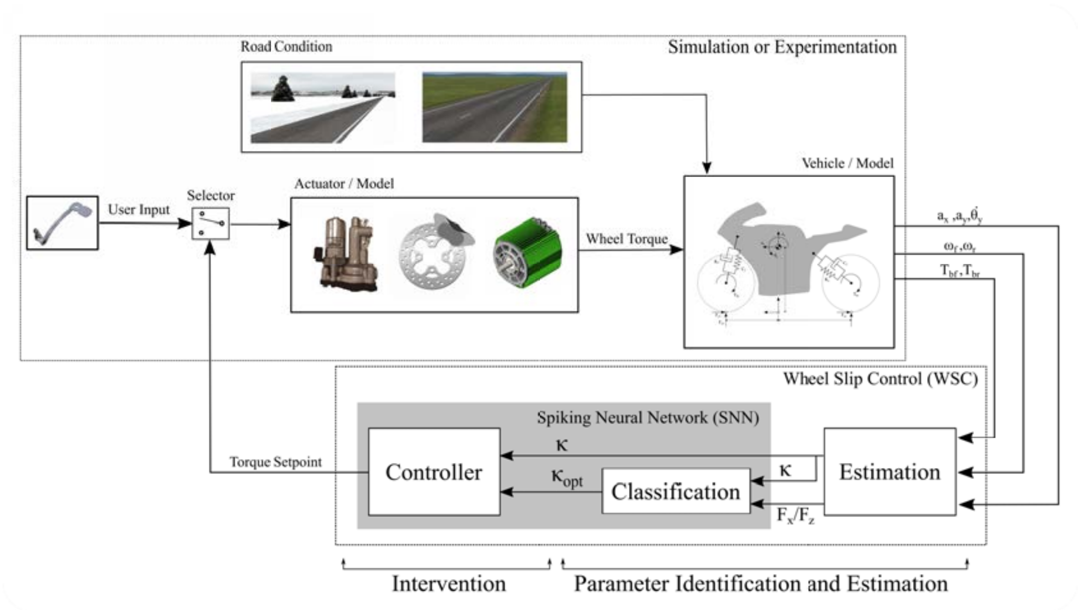


Figure 7. Wheel slip control (WSC) scheme

2.3. Estimation

The first block of the WSC is the estimation module. The estimation of the slip level of each wheel as well as the longitudinal grip ($\mu_{xi}=F_{xi}/F_{zi}$) are required to determine the type of road and to be able to control the vehicle. For this purpose, sensors installed in most modern vehicles, such as an Inertial Measurement Unit (IMU) and a speed sensor on each wheel, are used. In addition, the torque required at each wheel is also used. This torque can be determined in traction through the engine map and by measuring the hydraulic pressure of the master cylinder in braking processes. Knowing these variables and the dynamics of the system to be controlled, presented in previous sections, next, using an Extended Kalman Filter (EKF) to perform the estimation task is proposed.

The estimator linearizes the equations to obtain the internal variables of the system. Consequently, the vector of state variables (21), the vector of measured variables (22) as well as the control vector (23) is defined. The following equations can be derived for a four-wheeled vehicle.

$$x_k=[\mu_{xfl},\mu_{xfl},\mu_{xfl},\mu_{xfl},\kappa_{fr},\kappa_{rl},\kappa_{fl},\kappa_{rr}]^T \tag{21}$$

$$j_k=[\ddot{x},\dot{\theta},\Omega_{fl},\Omega_{fr},\Omega_{rl},\Omega_{rr}]^T \tag{22}$$

$$u_k=[T_{fl},T_{fr},T_{rl},T_{rr}]^T \tag{23}$$

The EKF assumes that the state variables (x_k) evolve in time as a function (24) which relates the previous state (k-1) to the current state (k), affected by a noise (w_k) with a zero mean and covariance Q. Similarly, it assumes that the measured variables (j_k) evolve as a function (25) that relates the state variables to the measured ones, also affected by white noise (v_k) with a zero mean and covariance R.

$$x_k=\phi_{k-1}(x_{k-1}, u_k)+w_k \tag{24}$$
$$j_k=h_k(x_k)+v_k \tag{25}$$

The function (ϕ_{k-1}) predicts a new state as a function of a previous state. Similarly, the function (h_k) predicts the measured variables as a function of the estimated state. To determine the value of both functions, it is necessary to use the equations of the vehicle model. Thus, the measured and state variables are taken out of the model equations. If the evolution of any of the variables is unknown, its previous value will be assigned, leaving its time evolution solved by using the Kalman filter itself. This strategy is called random walk. The Kalman filter estimates the state variables through a prediction and update based on a temporal model (24-25). Initially, it performs the a priori prediction of the subsequent state (26) and then a projection of the error covariance (27).

$$\hat{x}_k^*=\phi_{k-1}(\hat{x}_{k-1}, u_k) \tag{26}$$
$$P_k^*=\Phi_{k-1}P_{k-1}\Phi_{k-1}^T+Q \tag{27}$$

Next, the filter gain (28) is obtained. This gain is used to update the states (29), taking into account the measured variables (j_k) and the error covariance (30).

$$K_k=P_k^*H_k^T\left(H_kP_k^*H_k^T+R\right)^{-1} \tag{28}$$
$$\hat{x}_k=\hat{x}_k^*+K_k(j_k-h_k(\hat{x}_k^*)) \tag{29}$$
$$P_k=(I-K_kH_k)P_k^* \tag{30}$$

The Jacobians of the state variables (31) and measurement (32) are used to linearize the nonlinear equations of the system in the current state.

$$\Phi_{k-1}=\frac{\partial\phi_{k-1}}{\partial x}(\hat{x}_{k-1}) \tag{31}$$
$$H_k=\frac{\partial h_k}{\partial x}(\hat{x}_k^*) \tag{32}$$

The Jacobians can be precomputed or performed during the execution of the filter, increasing the computational cost in the latter case.

Another way to implement the Kalman filter is with a double structure that allows decoupling the kinematic and dynamic equations, providing greater

stability in the prediction although with a higher associated computational cost. This structure would estimate vehicle speed and calculate the slip level in the first stage. Next, in a second stage, it would estimate the vertical and longitudinal forces that allow obtaining the adhesion.
Finally, covariance matrices Q and R have to be properly determined to improve the Kalman filter performance. This way, to optimize the results obtained by the estimator, a genetic algorithm has been used to minimize the error. Real test data have been used for this purpose.

2.4.Spiking Neural Networks (SNN)

The determination of the type of road is carried out by the identification module of the WSC. This information will be an input to the last module of the controller, i.e., the intervention module. In this work, the identification and intervention modules are based on the use of Spiking Neural Networks. SNNs are considered the third generation of neural networks. In the new paradigm, the information is encoded by means of impulses. The main advantage offered by SNNs is the accurate reproduction of the behavior of biological neurons. This allows the implementation of biological learning methods that can only be applied to spike coding.
To interact with the environment, information must be encoded and decoded so that it can be processed by the neural network. Three types of neurons are defined according to their relationship with the environment: sensory neurons, interneurons, and motor neurons.
Sensory neurons are responsible for measuring environmental variables and transforming them into impulses to be subsequently processed by the network. Interneurons have no relationship with the environment. However, they play a fundamental role since they are the ones that establish complex relationships, modifying the response of the network to a sensory stimulus. This response is transformed into action by the motor neurons that connect directly with the biological actuators. For example, in a muscle, there is a large number of motor neurons acting on the muscle fibers to contract and extend the muscle according to its activity. Biological neurons are composed of the dendrite, the neuronal nucleus, and the axon. Similarly, these components are also reproduced to develop the aforementioned three types of spiking neurons. In the case of sensory and motor neurons, dendrites and axons are replaced by coding and decoding processes respectively, as shown in Figure 8.

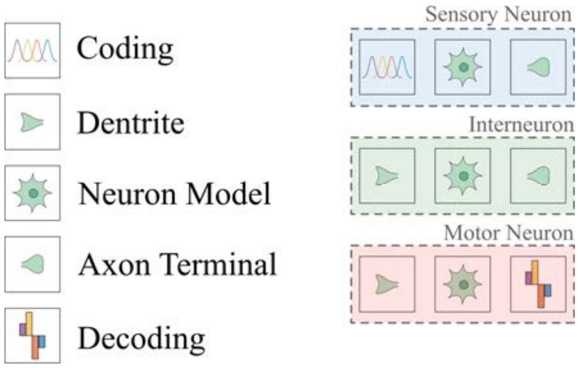


Figure 8. Neuron components and neuron configurations

In these networks, a stimulus is converted into a response through a neuronal pathway, performed by the link between an axon terminal and a dendrite, known as a synapse. It is responsible for establishing the strength of the link between neurons.
The use of spiking neural networks as well as the development of an innovative online learning strategy are the main contributions of this thesis. Therefore, the type of neuron and synapse used as well as their interconnection and learning algorithm are detailed first. Then, its application for classification and control applied to vehicular systems is descried.

2.4.1. Neuron Model

The neuron model used is the one proposed by Izhikevich since it offers a low computational cost without losing biological representation. This allows the use of biological learning algorithms suitable for integration into embedded hardware used for the control of passenger vehicles. The proposed model is composed of two differential equations (33) that model the neuronal membrane potential (v) as well as its recovery (u). For this purpose, it resorts to four parameters {a,b,c,d} that define the neuronal firing response.

$$\begin{cases} \frac{dv}{dt} = 0.94\ v^2 + 5\ v + 140 - u + I(t) \\ \frac{du}{dt} = a\ (b\ v - u) \end{cases} \tag{33}$$

$$\text{If } v \geq 30 \text{ mV then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \tag{34}$$

When a firing occurs, that is, when the membrane potential exceeds a certain threshold, the neuron resets its values according to the function (34). The neuronal model converts a level of direct current (I(t)) coming from the synapses into electrical impulses that travel along the axon to the next neurons. Figure 9 shows different responses obtained by varying the parameters {a,b,c,d}. Both the firing frequency and the bundling of the firings vary. To ensure a fast response as well as low distortion in the processed signal, a fast-spiking response is required.

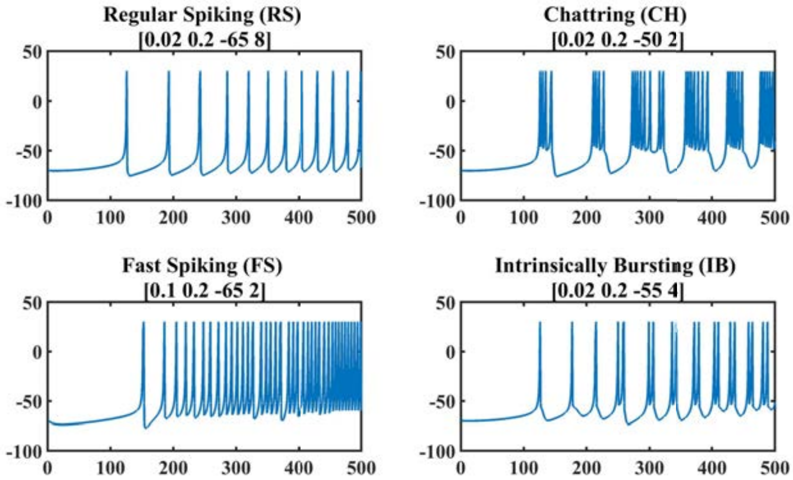


Figure 9. Neuron ramp response for different parameters [a b c d]

2.4.2. Synapse Model

The synapse models the connection between two neurons. This process converts the electrical impulses coming from the presynaptic neuron into the input current to the postsynaptic neuron. Biological mechanisms use neurotransmitters for this procedure. These neurotransmitters are released with the arrival of an impulse. Eventually, a high concentration of them opens channels in the dendrites, allowing the flow of current into the postsynaptic neuron. Both the number of channels and the concentration of neurotransmitters regulate the strength of the synaptic connection as well as its temporal response. This response can be almost instantaneous in the so-called electrical synapses which, unlike chemical synapses, have a minimal temporal response.

Neurotransmitter release is modeled using the response function (ε) as a relation to the time elapsed between impulses, where (t_i) is the time instant in which the last impulse occurred. The response function combined with the strength associated with each of the neuronal connections (w_{ij}) determines the input current according to (35), where i is the presynaptic neuron and j is the postsynaptic neuron.

$$I(t)=\sum w_{ij}\ \varepsilon(t-t_i)=\sum w_{ij}\ \varepsilon(\Delta t) \tag{35}$$

The response function model can be solved by reproducing the conductance of the synaptic junction through its temporal response (36) or by using a first-order system (37).

$$\varepsilon(\Delta t)=\begin{cases}\frac{\Delta t}{\tau_S}e^{1-\frac{\Delta t}{\tau_S}}, & \text{if } \Delta t>0\\ 0, & \text{if } \Delta t<0\end{cases} \tag{36}$$

$$\frac{d\varepsilon(\Delta t)}{dt}=-\frac{\varepsilon(\Delta t)}{\tau_s}+\delta(\Delta t) \tag{37}$$

However, none of these methods resemble the biological description based on channels that open and close in time with the arrival of impulses. For this purpose, a series of finite channels that model the response function as the sum of the conductivity in each of the activated channels are proposed (38). Since the number of channels is finite, they are reused once the conductivity is low or a new impulse arrives, for which the time of the impulse associated with each channel is defined according to (39).

$$\varepsilon(\Delta t)=\sum_{k=1}^{n}\left(\frac{\Delta t^k}{e\,\tau_S{}^2}e^{1-\frac{\Delta t^k}{\tau_S}}\right) \tag{38}$$

$$\begin{cases} t_i^k=\begin{cases} t_i^k, & t_i \sim= t\\ t_i^{k-1} & t_i= t\end{cases} \quad \{k\in N|\ 2\leq k\leq n\}\\ \qquad t_i^1=t_i\\ \Delta t^k=t-t_i^k \quad \{k\in N|\ 1\leq k\leq n\}\end{cases} \tag{39}$$

Figure 10 shows a comparison of the three methods for a constant spike train. It shows how the response offered by the proposed model combines fast response with minimum oscillation. This behavior minimizes disturbances and speeds up the response of the controller.

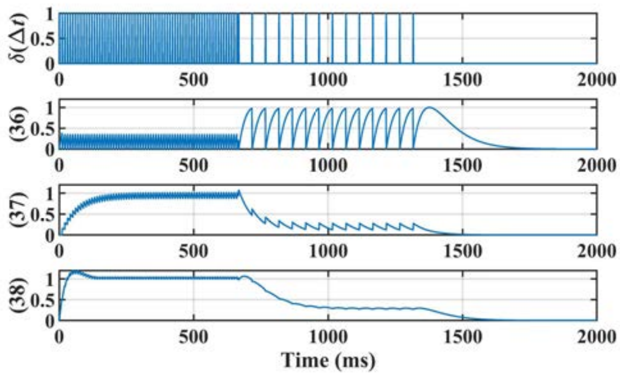


Figure 10. Comparison between synapse models according to equations 36, 37, and 38

Figure 11 shows the conductivity of a synapse modeled by a total of 8 channels for a continuous train of impulses. The channels become gradually occupied with the arrival of new pulses and are closed when they become obsolete. In addition, the state of each channel is plotted, relative to the conductivity curve

(36). In order to make the output value independent of the number of channels used, the sum of all channels is divided by the integral of the conductivity ($e\tau_S$), resulting in equation (38).

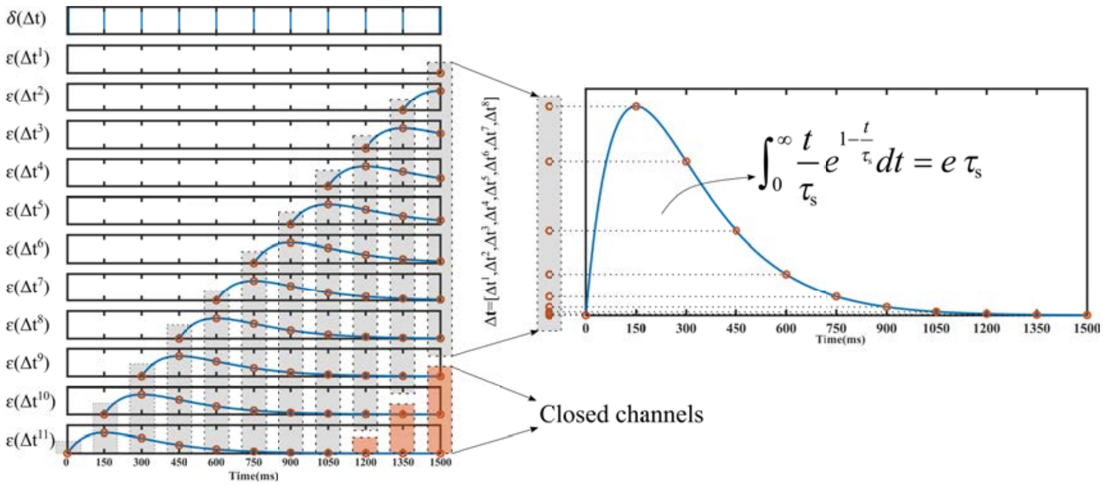


Figure 11. . Synapse model with 8 channels activated at the same time periodically

2.4.3. Coding and Decoding

Both the encoding and decoding processes are of crucial importance in order not to lose information during the transformation. Hence, they are studied independently below.

Sensory neurons are in charge of translating information from different sensors into electrical impulses. Different methodologies exist depending on how to encode the information in the impulses. The time between pulses and the firing rate can be used to create a train of artificial pulses that encode the information. However, there is another option where the neuronal nucleus is used as a pulse generator, modulating the input current depending on the information to be encoded. This thesis proposes using the latter method since it also allows utilizing the concept of 'summation', where the information is not only encoded temporally but also spatially.

Thus, the input variable (u) is encoded in a current value (I(u,i)) for a given number of sensory neurons (i). A set of Gaussian bells (40) distributed in the input space along the entire range of (u) in a linear way (41) is in charge of generating the current for each neuron. According to the distribution factor (β) (42), one or more neurons are activated at the same time for a given input value (Figure 12a).

$$I(u,i)=I_{max}\, e^{\frac{-(u-\mu(i))^2}{2\,\sigma^2}} \tag{40}$$

$$\mu(i)=I_{min}+(i-1)\,\frac{\sigma_c}{\beta} \tag{41}$$

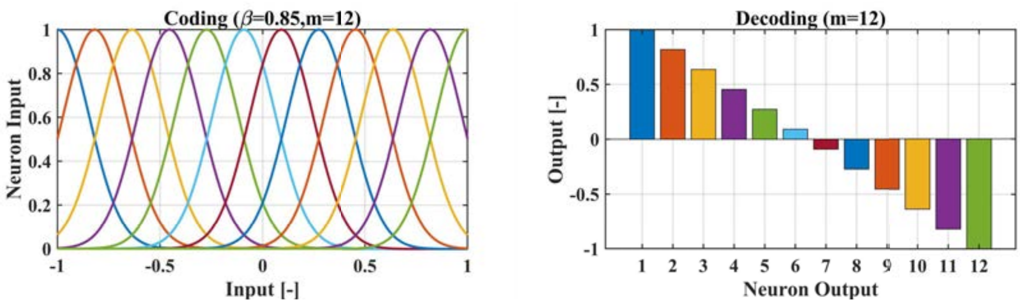
$$\sigma_c=\beta\,\frac{I_{max}-I_{min}}{m-2} \tag{42}$$

On the other hand, motor neurons are responsible for converting the neuronal output current into processed information. This information is decoded in the form of stimuli, in biological actuation systems such as muscles composed of fibers. This stimulation is responsible for contracting the muscle to perform an action. To this end, this thesis proposes using the synapse to obtain the stimulation current associated with each neuron. Then, the current of all motor neurons is added up, taking into account the distribution used for coding (β). Each neuron is associated with a gain in the same way, as proposed by Henneman's size principle. Each motor unit has an associated action capacity so they complement each other.
The decoding, in the same way as in the encoding, is performed linearly (Figure 12b) according to equations (43) and (44). Finally, the resulting value is obtained as the sum of the intensity coming from the synapse of each motor neuron multiplied by the gain of each motor unit (45).

$$\mu(i)=I_{min}+(i-1)\frac{\sigma_d}{\beta} \tag{43}$$

$$\sigma_d=\beta\frac{I_{max}-I_{min}}{m-1} \tag{44}$$

$$y=\sum_{i=1}^{m} I(i)\mu(i) \tag{45}$$



a) b)

Figure 12. a) Coding and b) decoding procedures

It can be observed (Figure 13) how the signal maintains the information after passing through the network if encoding and decoding are applied by assigning a neuron to a neuron without cross-connections. In this example with only 4 neurons, high-frequency noise can be observed in the reconstructed signal due to the decoding process and the frequency at which the firing occurs. A larger number of neurons is required to avoid this distortion and thus reduce the signal to noise ratio.

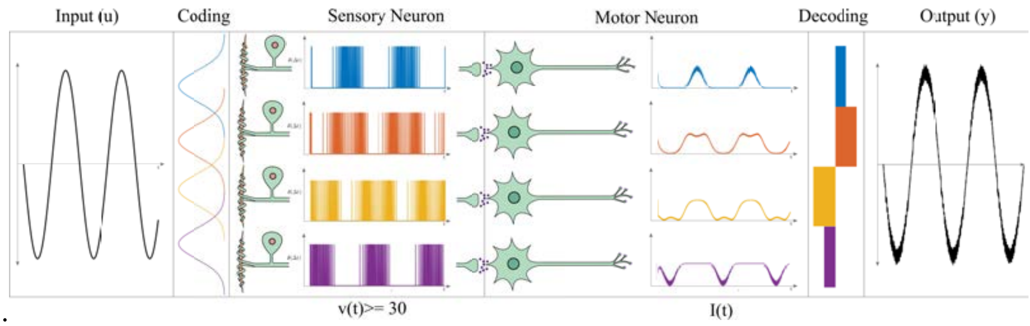
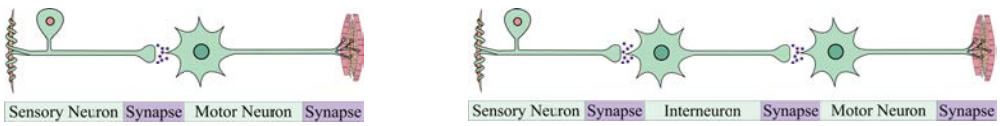


Figure 13. Coding and decoding implemented in a (4x4) neuronal network

2.4.4. Neural Path

Neural pathways are responsible for establishing the relationships that allow neural networks to perform highly complex tasks. These tasks are achieved by means of interconnected structures with a large number of neurons. Consequently, figuring out the connections as well as their behavior are highly complex tasks that require many years of work behind the mapping of neural areas. Thus, the work performed is based on biological mechanisms that are simpler and easier to recognize. This is the case of the Aplysia and structures in humans that do not require a large number of neurons, such as those related to reflexes.

The simplest neuronal pathway consists of a single synaptic link between a sensory and a motor neuron. In this so-called monosynaptic connection (Figure 14a) the information travels from the sensory receptors, represented by the encoding, to the motor units, typically muscular, represented by the decoding. This type of binding leads to a direct reaction to an action. Such a link can be found in the mechanism of reflex actions that require an immediate response to a stimulus in order to avoid danger. One of the cases always used as an example is the patellar reflex, which, after receiving a blow on the knee, makes the leg rise quickly due to a monosynaptic binding. However, this reflex is not only associated with a monosynaptic connection but is also constructed using polysynaptic connections (Figure 14b). This reflex, by means of an interneuron, inhibits the muscle opposite to the one stimulated by the monosynaptic junction. Therefore, the pathways of reflex arcs allow us to understand how a network behaves in response to certain stimuli. More complex reflex structures have to be studied to analyze networks in charge of continuous control.



a) b)

Figure 14. Neuron connections: a) monosynaptic and b) polysynaptic

The Vestibulo-Ocular Reflex (VOR) is an example of continuous control found in animals besides humans. This reflex is responsible for maintaining a stable gaze during a horizontal head movement. This requires continuous control of eye position. This control is done according to the angle of the head obtained by means of the acceleration sensed by the semicircular canals.
The network that allows this control is composed of a large number of neurons. However, it can be simplified according to functional units as shown in Figure 15. The control mechanism is similar to the one used in the patellar reflex, where two antagonistic muscles are stimulated by an inhibitory and excitatory junction. This network is in charge of changing the point of equilibrium of the muscles acting on the eye. The proposed control structure that maintains the closed-loop equilibrium is described in the following sections. This structure is developed on the principle of antagonistic action obtained from the analysis of reflexes.

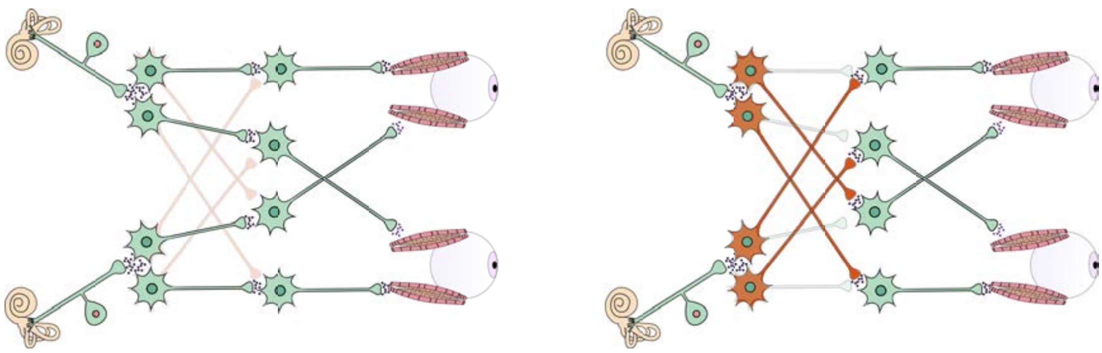


Figure 15. Simplified VOR reflex arc excitatory (left) and inhibitory (right)

2.4.5. STDP Learning

Despite using a connection similar to those found in nature, a learning process is required to adjust the strengths of the synaptic connections. This process allows adjusting the behavior to a particular system. There are several learning methods, most of them coming from adaptations of algorithms for ANNs. However, these algorithms are not based on biological mechanisms. They use mathematical optimization algorithms to minimize the error committed by the network. Sometimes optimization algorithms based on natural behavior are used, such as those based on evolution or genetic co-evolution. However, these learning mechanisms are not based on neuronal plasticity and do not reproduce learning between biological neurons faithfully.
This thesis aims to use a learning mechanism based on neuronal plasticity using Spike-Time-Dependent Plasticity (STDP). This methodology resorts to the synchronization of pre- and post-synaptic neurons to determine the type of strengthening that the synaptic linkage receives (46). The synapse is modeled

as a function of the time between firing (τ) by offering Long-Term Potentiation (LTP) or Long-Term Depression (LTD) so that the synaptic strength is increased or decreased, respectively. This response is defined by the so-called STDP rule.

$$\tau = t_{post} - t_{pre} \tag{46}$$

In biological systems, different STDP rules are found depending on the activity performed by each neural network. Thus, Hebbian type learning using LTP for $\tau>0$ and LTD for $\tau<0$ coexists with anti-Hebbian learning, involving inverted behavior and rules where there is always LTD or LTP for $\tau<0$. Out of all combinations, a Hebbian rule (47) is used for classification while All-LTP is employed within the control network (48).

$$STDP(\tau) = sign(\tau) e^{-\frac{|\tau|}{\tau_{STDP}}} \tag{47}$$

$$STDP(\tau) = e^{-\frac{|\tau|}{\tau_{STDP}}} \tag{48}$$

Both of them (Figure 16) are associated with the same type of application in similar structures found in the brain. To extract information or patterns, a Hebbian rule is more appropriate, whereas STDP rules of the All-LTP type are more suitable for the realization of control with high firing frequencies.

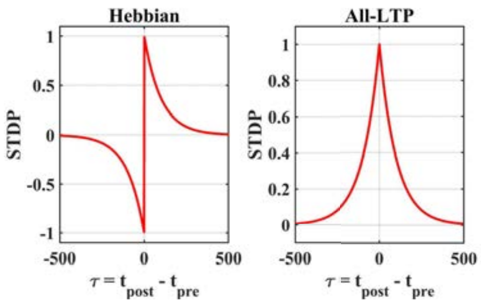


Figure 16. Hebbian and All-LTP STDP rules

To integrate STDP with a supervised learning-based control scheme, it is necessary to modulate its effect to define the evolution of synaptic strength. The error between the output and the desired target is used to modulate the learning, just as dopamine is released in a biological system. Thereby, the time evolution of both the STDP rule (49) and the error (50) is defined. Each of them is assigned to a time constant (τ_C and τ_D respectively) that regulates its delay in its application. The modulation is produced using equation (51).

$$\frac{dC}{dt} = -\frac{C}{\tau_C} + STDP(\tau)\delta(t - t_{pre/post}) \tag{49}$$

$$\frac{dD}{dt}=-\frac{D}{\tau_D}+error(t) \tag{50}$$
$$\frac{dS}{dt}=C\ D \tag{51}$$

In addition, it is also necessary to define the eligibility (g) to reproduce the time evolution of the synaptic forces. This is a biological phenomenon in which the connections with higher efficiencies have to undergo greater changes. This is regulated according to (52) and constants (g_1) and (g_2). Finally, the weights are modified in each iteration according to (53), where the eligibility and modulation define the growth for each synaptic strength. Furthermore, a learning constant (μ_l) is included in order to cause a higher or lower impact on the synaptic strengths while maintaining a trade-off between convergence and learning speed. Additionally, it can be multiplied by the presynaptic current (I_i) to increase the potentiation in the connections with higher currents.

$$g(w_{ij})=1-g_1^{\frac{-g_2 abs(w_{ij})}{w_{ij,max}}} \tag{52}$$
$$w_{ij}(t)=w_{ij}(t-\Delta t)+\mu_l\ dS\ g(w_{ij}(t-\Delta t))I_i \tag{53}$$

This rule must be constantly updated when a new firing occurs. Consequently, the presynaptic or postsynaptic neurons allow the modification of the synaptic connection as shown in Figure 17. When the network consists of more than one neuron per layer, the neuronal connections are represented in a matrix form and the STDP rule is associated with another one of equal dimensions. This allows matrix operations to solve the learning of a large-size network without increasing the complexity of the learning algorithm.

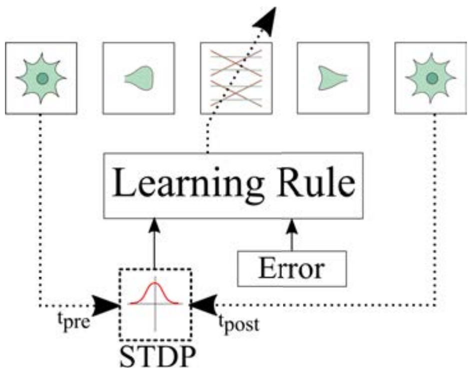


Figure 17. STDP learning scheme using error and STDP rule

2.4.6. Classification

A neural network based on SNN is proposed for road type classification tasks. In order to detect the type of road, the information provided by the EKF estimator is used. Specifically, it uses the level of slip and grip experienced by each wheel. The information required by the controller is the optimal slip, so this is the variable to be identified. Therefore, the determination of all parameters defining longitudinal contact dynamics (15) is not necessary.

Figure 18 shows the input data set (κ,μ) for 4 different conditions modeled with various parameters $\{D_x, C_x, B_x, E_x\}$.

The contact condition can easily be determined by distinguishing the difference between the four curves. Only for the case of low slip, two of the curves overlap, which makes it very difficult to distinguish them. This is not a problem for a WSC type controller since the classifier always works with medium or high slip levels.

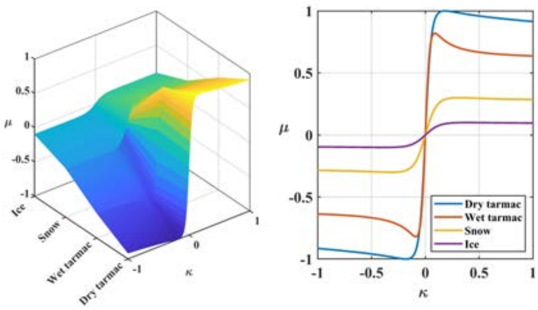


Figure 18. Tire data for different road-tire dynamics

Although the classification to be performed is not very complex, it is necessary to set up a neural structure where interneurons are present. Consequently, there is at least one hidden layer that endows the neural network with a high capacity for pattern differentiation. In this particular case, it will associate an optimal sliding level to each road condition. The classification does not start from a prefixed structure since it is difficult to find one with similar characteristics in nature. Therefore, a fast-spiking neural network (Figure 19) with a single hidden layer consisting of 20 sensory neurons (10 per input), 15 interneurons, and 10 motor neurons is used. Initially, the synaptic links are fully connected with random values. This type of structure is widely used in ANN classification networks.

However, the learning method is different from the traditional one found in artificial networks since STDP-based learning is applied.

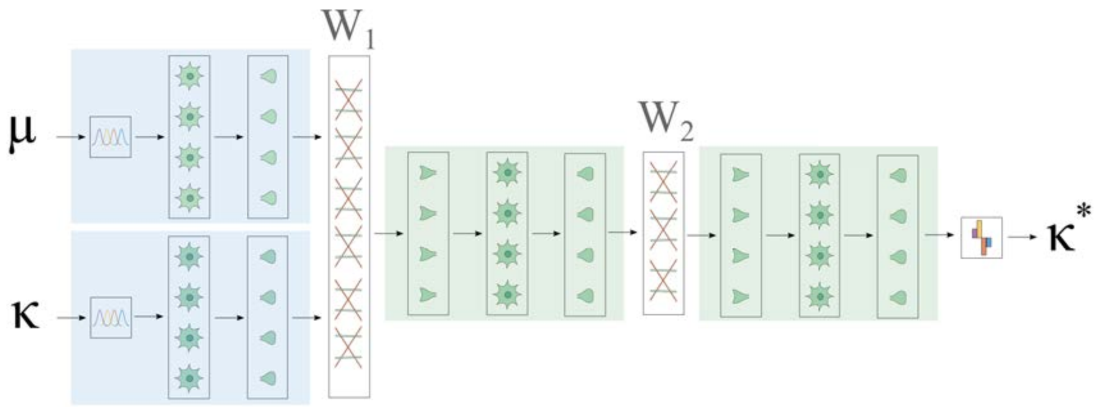


Figure 19. Classification neural network

Learning is performed offline with a training and validation data set consisting of the input pair (κ,μ) and the optimal sliding (κ) as the learning target.
The STDP rule used is the Hebbian type as it is the one found in cerebral regions where tasks associated with detection and classification are reproduced.

2.4.7. Controller

As far as the controller in biological systems is concerned, networks with similar functionality can be found. The connections and synaptic strengths of these structures inspired by reflex arcs are tuned and modified to ensure stability during operation depending on the task assigned. The selected control scheme is the Equilibrium Point Hypothesis (EPH), as previously discussed, which is one of the two control theories for biological control. Concretely, EPH can be observed in reflex arcs such as the Vestibulo-Ocular Reflex (VOR). Other biological systems, such as the control of an arm, can be explained with this approach. The Central Nervous System (CNS) sets a target for the position of the arm and the proposed neural circuit (Figure 20) controls the two antagonist muscles. This structure is inspired by the continuous control of the VOR as well as the threshold-based scheme of the EPH.
A similar control structure can be applied to Wheel Slip Control (WSC). Based on the optimal slip obtained by the classification neural network and the current slip estimated by the EKF, the proposed control neural network provides the torque setpoint. The controller is responsible for increasing or decreasing the torque on the wheel depending on whether the threshold imposed by the optimum slip is exceeded or not reached.

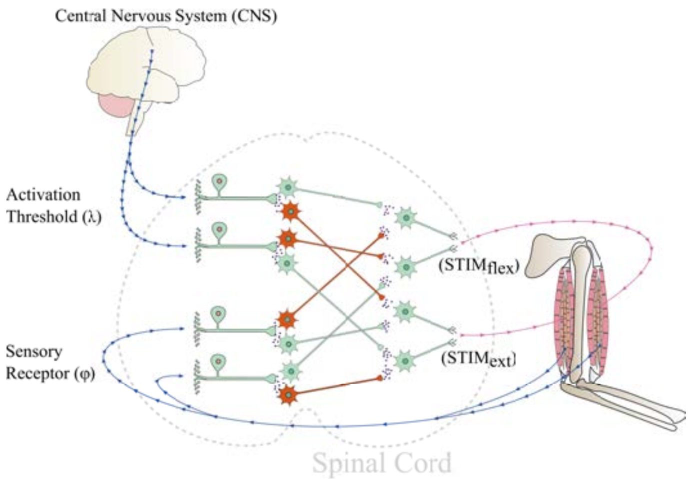


Figure 20. Arm Controller based on Equilibrium Point Hypothesis (EPH)

Figure 21 presents the neural connections using the minimum number of neurons possible to perform the control. Each neuron is assigned to a variable and a certain sign. This way, control can be performed with only 6 neurons. It is noteworthy that, as observed in the encoding and decoding process, a greater number of neurons minimizes the noise in the control signal. Thus, for proper operation, it is necessary to increase the number of neurons while maintaining the same neuronal connections, thus distributing the strength of the synapse among the number of connections made.

The excitatory and inhibitory neuronal connections as well as the strength of each connection enable the implementation of the dual antagonistic neuron approach. These neurons are responsible for increasing or reducing the torque exerted on the wheel. This allows the torque to be continuously modulated, detecting whether we are above or below the threshold. This ensures the stability of the controller, allowing its adaptability during operation without the risk of becoming unstable.

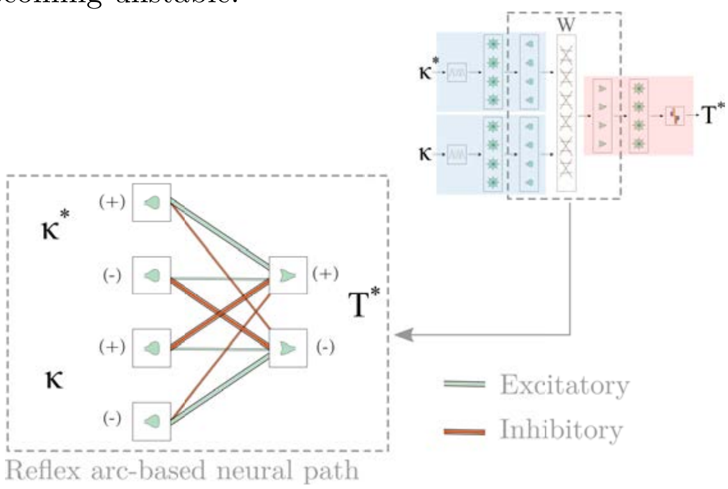


Figure 21. Control structure used based on reflex arcs

During training, the controller can face an abrupt or slight response which results in a non-optimized slip control. The learning algorithm is in charge of adjusting the synaptic forces to find an optimal solution. To do so, it employs STDP learning, modulated by the difference between the optimal slip and the actual slip. The rule used in this case is all-LTP since it is the one found in brain regions focused on motor control as well as with a high firing frequency. The type of neuron used is fast-spiking, updated to 100Hz frequency, which is a commonly used frequency for controllers in vehicles with WSC.

The WSC structure using EKF and SNN is presented in Figure 22. This structure is based on a four-wheeled vehicle model. It can be seen how all the elements described in the methodology are combined to maximize the longitudinal forces. In addition, it can be observed how the structure of the classification network is integrated in the control network since the output of one is the input of the other, so there is no need for intermediate decoding and coding. The learning algorithm is only applied to the control network. This is because the classification network is trained offline while the control network is able to adapt during its normal operation thanks to its fixed bio-inspired structure.

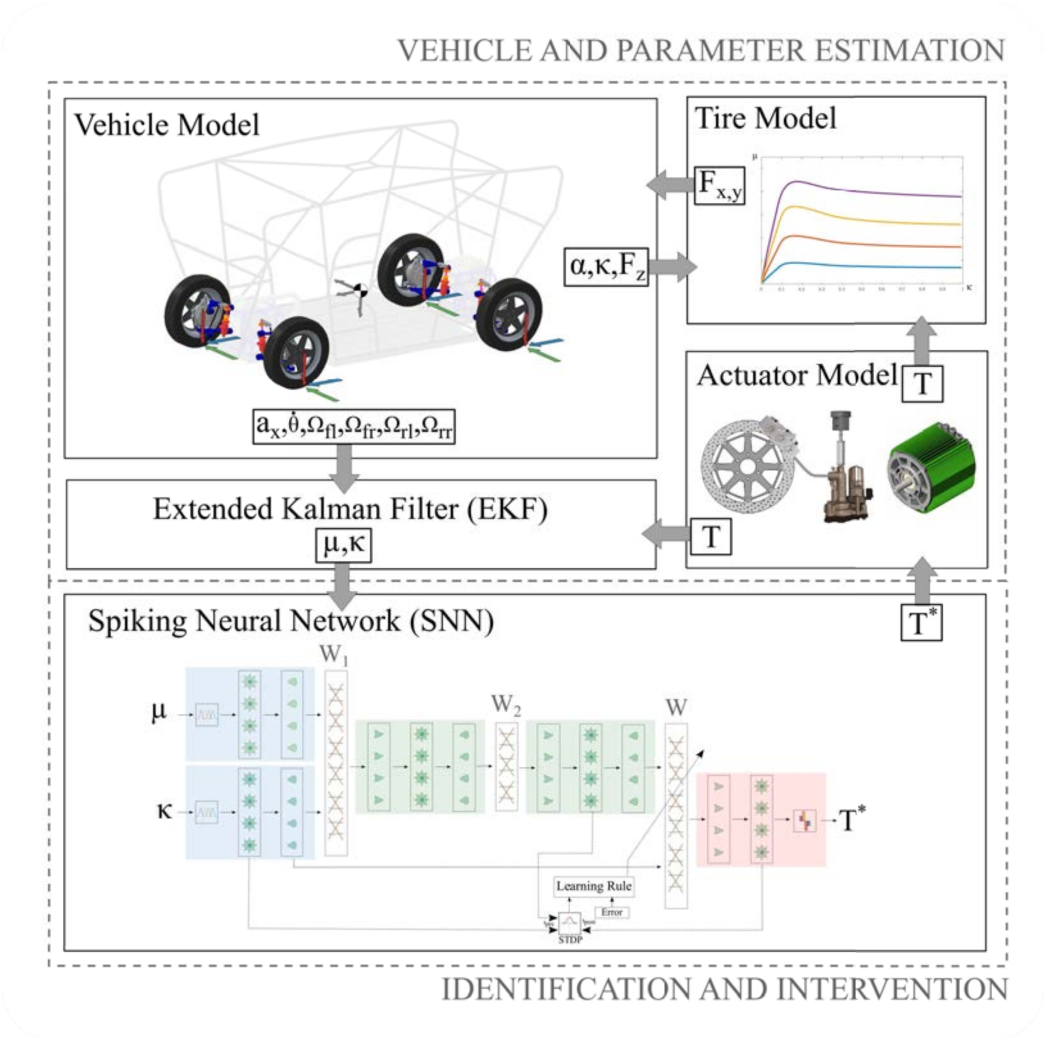


Figure 22. WSC structure using EKF and SNN

3. Results and Discussion

The proposed control structure developed in this thesis has been tested by means of simulations and real tests conducted on experimental vehicles. Results suggest that controllers based on the use of spiking neural networks can be a viable and robust alternative. The stability and performance of the developed controllers have been confirmed in the tests. In addition, the estimation algorithms and learning strategy have also shown adequate behavior. All in all, the proposed algorithm can be used to perform the control of active safety systems. This chapter includes the results of the simulations and real tests as well as a comparison with main competitors.

3.1. Parameter identification and estimation module

The simulations performed for the validation of parameter identification and classification are presented below. These results involved both two-wheel and four-wheel vehicles. Simulations with a change of adhesion during braking, using both fuzzy logic and an SNN-based control algorithm, has been carried out. Thus, it is possible to evaluate how the estimations adapt during a sudden change of contact conditions.

3.1.1. Two-wheeled vehicle

Three emergency braking processes have been performed, using the ABS control algorithm based on fuzzy logic proposed [3]. The first two simulations reproduced changes in road type during braking by increasing the adhesion of the road (Figure 23) and decreasing it (Figure 24). The latter was repeated without considering the dynamics of the actuation system (Figure 25). For the calculation of longitudinal forces and speeds, a Kalman filter was used with the approach presented in previous sections. However, in this case, another EKF was used for the identification of the road type. The EKF used the previous estimates as input. It provided the maximum adhesion level of the road, using a simplified tire model, as output.

Simulations performed on the two-wheeled vehicle have demonstrated the effectiveness of the EKF in estimating both vertical and longitudinal forces. As it is observed, during braking on a high grip road with a two-wheeled vehicle with a high tendency to pitch, low values of vertical load can be observed on the rear wheel. Equations used in the estimator do not take into account this effect as well as the wheel lift-off, which leads to larger errors in these conditions. Nevertheless, the application of the EKF as an estimator is properly validated.

Regarding road estimation, the use of a tire model, despite being its simplified version, introduces an increase in the computational cost of the estimator. Furthermore, since the model is highly nonlinear and the EKF linearizes for each state, there is a slow response of the estimator to a change in dynamics. This is observed both at the beginning of the test and during a transition where the response of the estimation is slow. This is the main reason for proposing another method for the identification of the road type. For this purpose, the use of SNN is proposed as a classifier. This new strategy makes use of the data obtained by the EKF to provide a direct and faster response.

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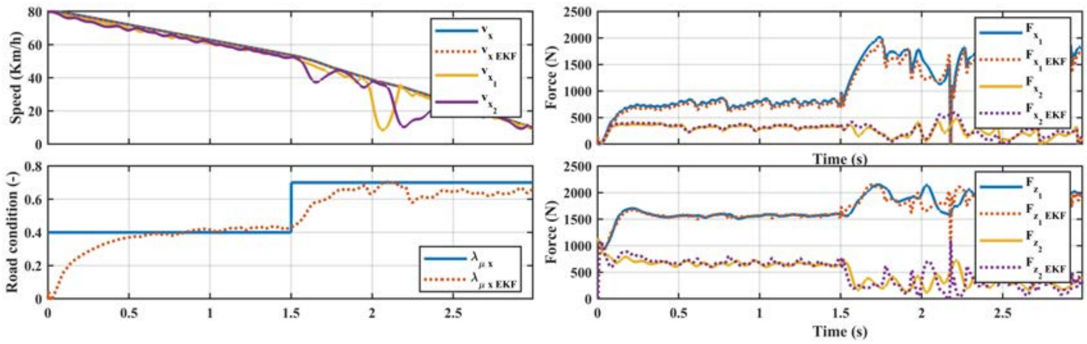

Figure 23. Low-high road change simulation results (Speeds, road type and forces)

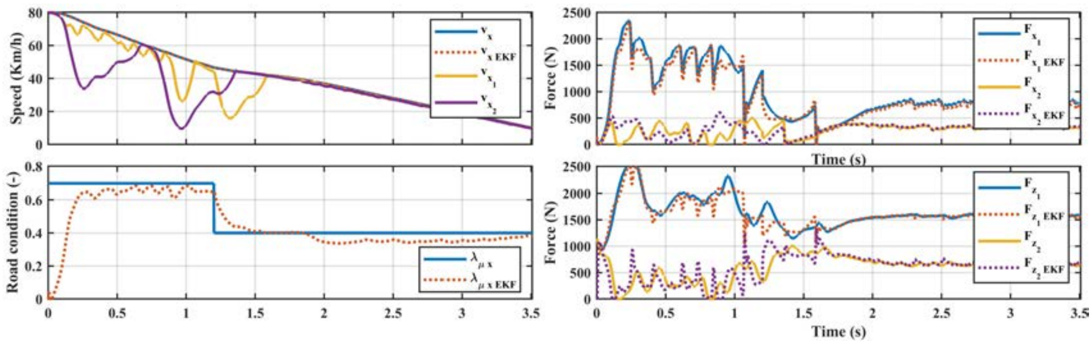

Figure 24. High-low road change simulation results (Speeds, road type and forces)

To emphasize the importance of correct modeling of the transient response of the actuators, the dynamics of the braking system have been omitted. This includes the pump that generates the pressure as well as the fluid dynamics in the brake line. Figure 25 presents the results of this non-realistic braking test. It can be observed that the controller is able to succeed in reaching slip levels close to the optimum without the presence of any oscillations. However, this simulation is not reliable. This type of incorrect response can be found in literature, highlighting the importance of performing experimental tests to validate the simulations in terms of vehicle control. Next, the proposed control algorithm will be tested in the following section.

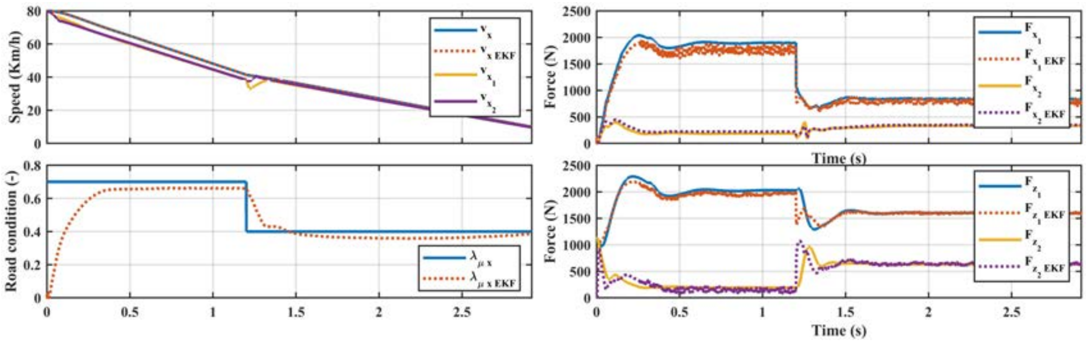

Figure 25. High-Low road change simulation results (No brake Dynamic) (Speeds, road type and forces)

3.1.2. Four-Wheel vehicle

As with the two-wheeled vehicle, simulations were carried out for emergency braking with a change in the level of adhesion. In these simulations, the right and left wheels experience the same grip level. In this case, a change from a low to a medium grip level (Figure 26) and another with the reverse situation (Figure 27) were performed. For the estimation of the forces of each wheel, the EKF was used in the same way as in the previous section, only changing the model from two to four wheels. In this case, a classification neural network based on SNN was used for the identification of the road type. This network provided the optimum slip level associated with the road on which the vehicle was being driven as output.

The estimated forces on each wheel as well as the longitudinal speed of the vehicle were estimated with reduced fluctuations.

Regarding the classification performed by the SNN, a fast response is observed since it does not require the updating of states. The estimation is also stable despite possible fluctuations in the forces caused by the control algorithm or by tracking errors of the EKF. During transitions, changes in the classifier output can be observed, which is due to the change in tire dynamics. This estimation error only takes place in short periods of time. Therefore, the identification and estimation module is validated for all trained road types.

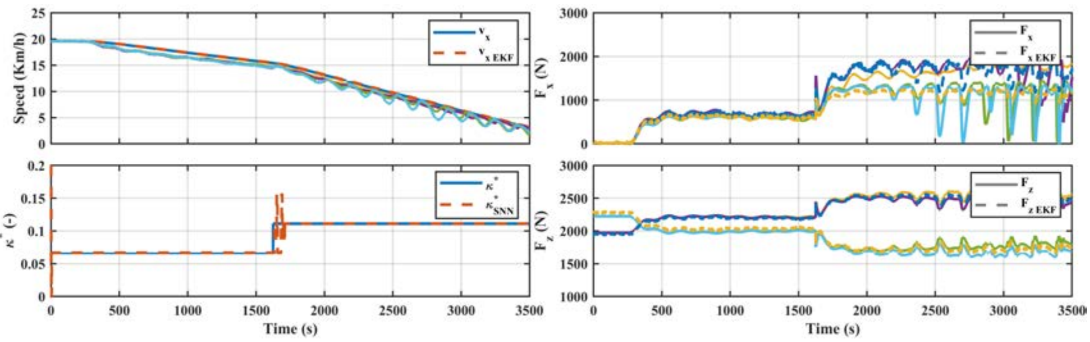

Figure 26. Low-medium road change simulation results (Speeds, optimum slip level, longitudinal and vertical forces)

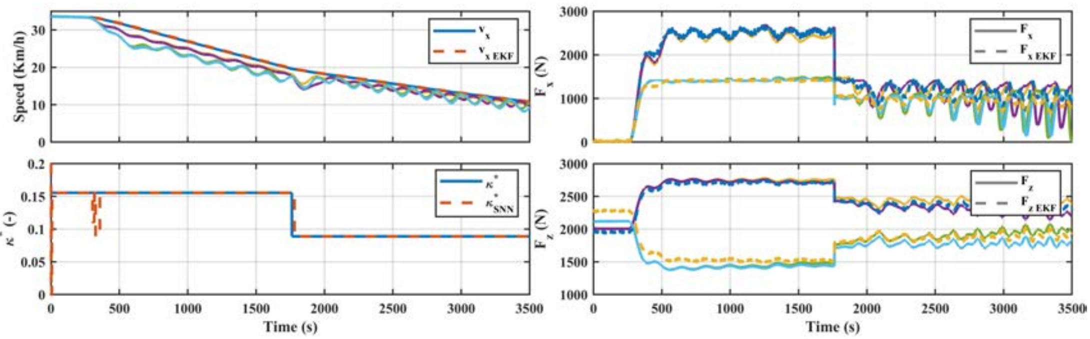

Figure 27. High-medium road change simulation results (Speeds, optimum slip level longitudinal and vertical forces)

3.2.Intervention module

To test the effectiveness of the control algorithm, two sets of simulations were performed. First, a nonlinear biological model was used to test the ability to learn during control, using supervised learning. Specifically, Hill's model of an arm joint was used. Secondly, after validating its behavior for a biological model, the module was tested on a vehicular system. This way, a four-wheeled vehicle was used to simulate an emergency braking with a change of adhesion.

3.2.1. Biological Control

In order to perform supervised learning in an arm joint, two types of sinusoidal position simulations were performed. The first one reproduced a process in which the neural network did not initially reach the setpoint signal. Subsequently, the learning algorithm sought to reduce the error. Next, a change in the dynamics of the joint is introduced after 20 seconds in a second simulation. This change modified the properties of the muscle and required the activation of learning to compensate for this event.

Figure 28 shows the time evolution of the first simulation performed. The angular position is achieved (Figure 28a) after 60 seconds of learning, which requires an increase in muscle stimulation applied to both the extensor and flexor muscles (Figure 28b). The learning mechanism, upon experiencing an error between the target and the measured position, increases the STDP modulation by dopamine signal D. As the error is decreased by learning, the modulation is reduced (Figure 28c) according to the temporal response. The firing pattern can be seen in Figure 28d. It can be observed that the same sequence is repeated when learning ends.

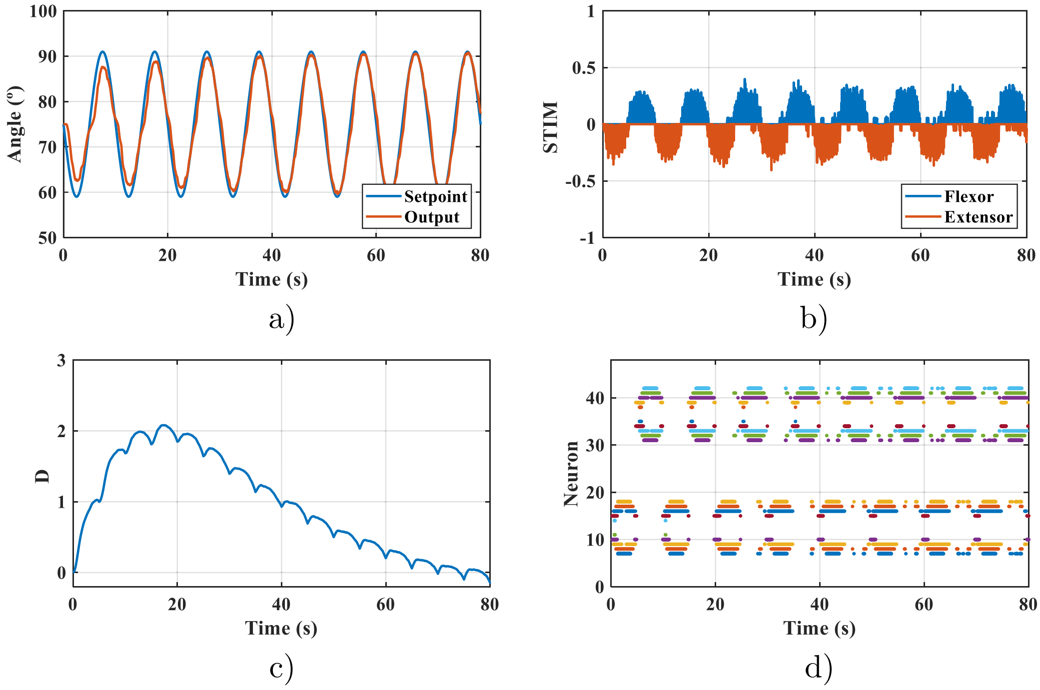

Figure 28. Learning process with a sinusoidal setpoint (a)Output response, b)Muscle stimulation, c)Dopamine level and d)Neural activity)

Next, results obtained in the second simulation where a change in the dynamics is introduced, are presented. Results with disabled (Figure 29a) and enabled (Figure 29b) learning are shown for comparison purposes. This test highlights the importance of a continuous learning algorithm when the dynamics of the system are variable. In such a case, this learning process compensates for the steady-state error produced by the asymmetry of flexor and extensor muscles. If learning is disabled, the dopamine level (Figure 29c) does not converge to zero because its modulation is not effective. However, when modulation is enabled, its effect on synaptic strengths corrects the defect by converging to zero (Figure 29d).

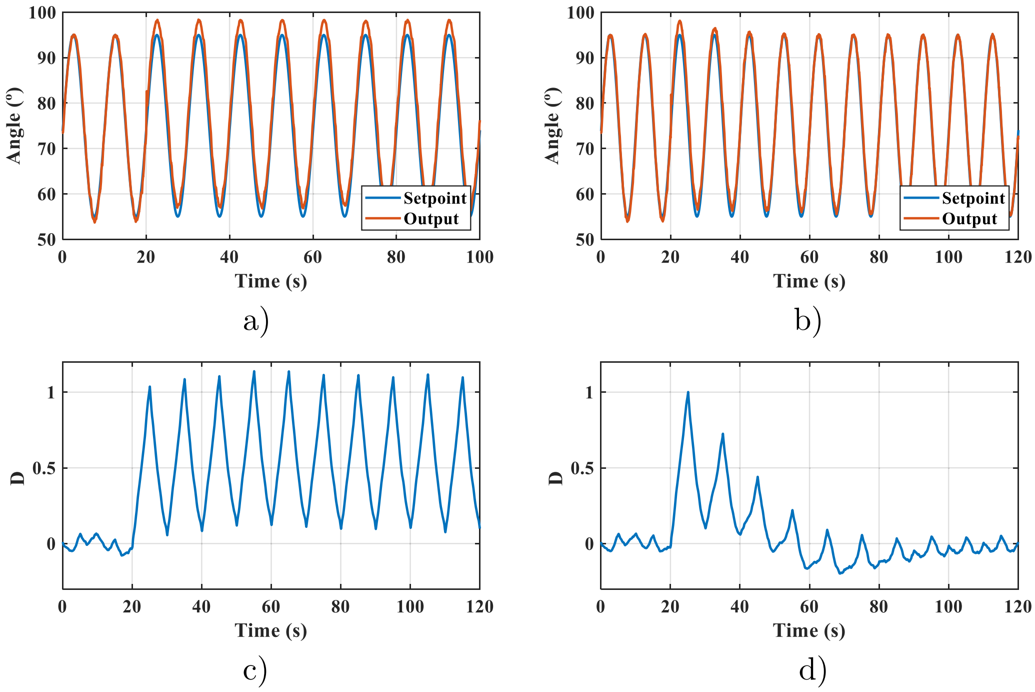

Figure 29. Behavior in the face of a change in system dynamics without (a,c) and with activated learning (b,d) ((a,b) Output response, (c,d) Dopamine level)

3.2.2. Vehicle control

The learning algorithm, once validated in a biological-like control system, was integrated into the control scheme of a vehicle to evaluate its correct operation. Simulations consisted of reproducing emergency brakings on roads with constant and changing adhesion coefficients to demonstrate the effectiveness and robustness of the proposed algorithm. The algorithm was then responsible for increasing or decreasing the braking forces to minimize the committed slip error. The goal was to reduce the braking distance while ensuring maneuverability. Initially, the structure of the network was defined with inhibitory and excitatory connections in a bio-inspired way and with a reduced value of synaptic strength. It took a total of 20 iterations for the algorithm to converge to a state with a minimum dopamine level, achieving a reduced braking distance in this process, as shown in Figure 30.

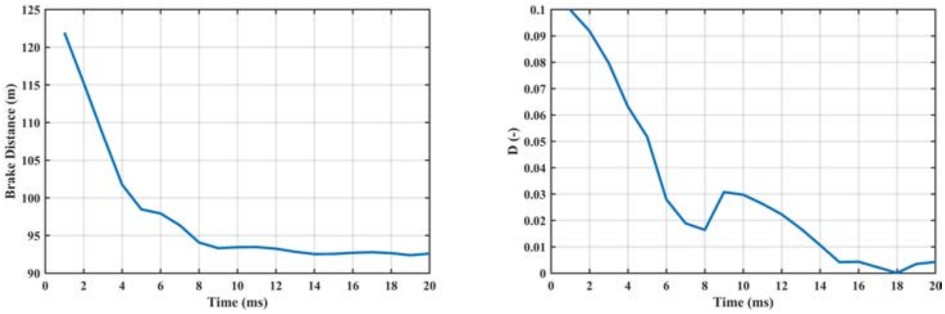

Figure 30. Distance (left) and dopamine (right) level during the supervised learning process

Both Figure 31 and Figure 32 show the velocities and pressures, respectively, in iterations 1, 10 and 20 of the learning process. It can be seen that in iteration 1 the response of the network is not sufficient to generate the longitudinal braking force required to achieve the desired slip level, which leads to a high braking time. Interestingly, it is observed that the algorithm shows a fast adaptation of its response after the surface. This fact can be observed throughout the whole learning process, showing the robustness and adaptation capability of the algorithm. Iteration 10 shows a response with higher slip levels than at the beginning of the learning process. However, different behavior between the front and rear wheels is observed. This way, the algorithm is improving its performance but has not managed to adapt its response completely to the load transfer yet. Although the braking time is becoming shorter, the error is still high, so the learning process continues.

Finally, in iteration 20, the associated value of dopamine (D) (Figure 33) is low and the error has been minimized. In these conditions, the braking time is the shortest one. Furthermore, it is observed that the front and rear wheel speeds experience a similar slip level, which demonstrates the satisfactory performance of the algorithm and results in the finalization of the learning process.

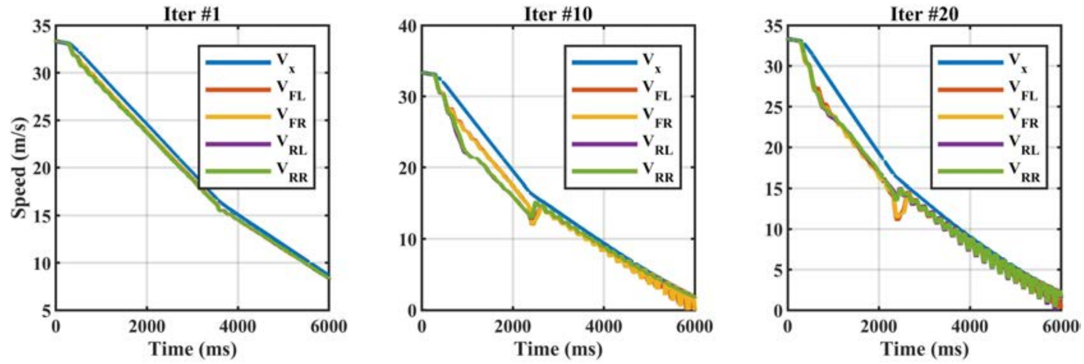

Figure 31. Vehicle speeds under a supervised learning process (20 iterations)

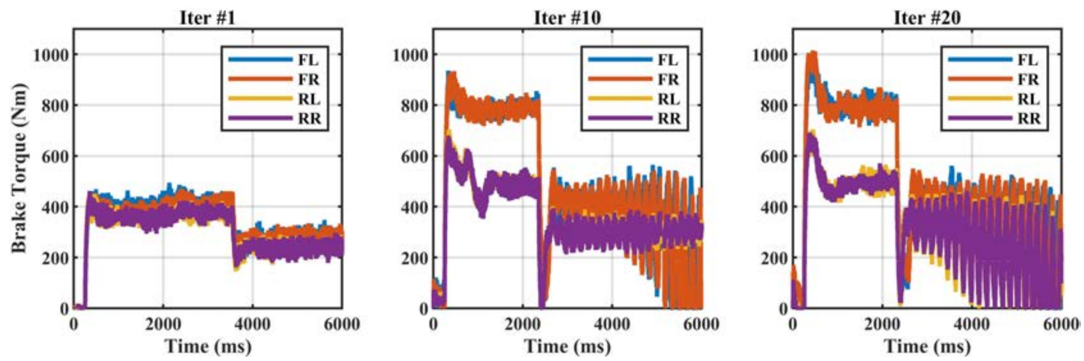

Figure 32. Braking torque under a supervised learning process (20 iterations)

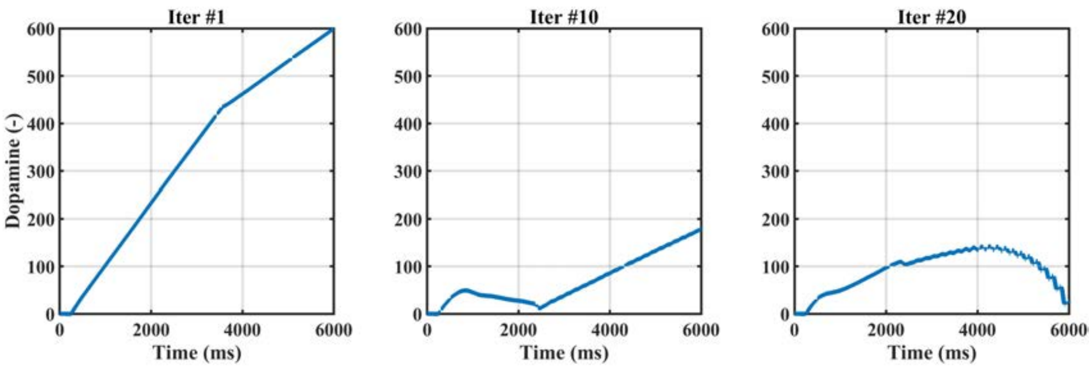

Figure 33. Dopamine level under a supervised learning process (20 iterations)

Previous results confirm the viability of the proposal. However, a single test is not enough to verify the proper behavior of the learning algorithm and the performance and stability of the controller. Thus, it is required to carry out a higher number of simulations in different braking conditions. In addition, it is desirable to have an objective way to quantify the performance on the different surfaces proposed. With this objective in mind, performing a higher number of simulations is proposed, using the so-called Key Performance Indicators (KPIs) presented below, as references.

3.2.3. Key Performance Indicators (KPIs)

KPIs are used to evaluate the performance of WSC based controllers. There is a large number of indicators available depending on the variable to be evaluated and its impact on safety, maneuverability, comfort, durability and so on. In this case, only the KPIs focused on emergency brakings have been selected. Other KPIs, such as those related to the comfort and durability of the actuators, have been omitted considering that, in an emergency situation, the priority is to maximize grip without losing control of the vehicle.
KPIs are divided into steady-state and transient-state ones, both of which will be used to analyze the response of the proposed controller. In addition, a comparison with the conventional ones based on slip threshold control proposed by vehicle components manufacturer Bosch has been included.

.<u>ABS Index of Performance (ABSIP)</u>
This KPI is used to compare the braking distance obtained by the controller when the ABS is deactivated and a full skid is produced (54). Thus, the overall effectiveness of the controller is obtained.

$$\mathrm{ABSIP}=\frac{d_{ABS}}{d_{SKID}} \tag{54}$$

<u>Peak To Peak PTP (PTP)</u>
It measures the agility of the controller response. To this end, the variation of the maximum angular velocity during the first cycle (max) concerning the reference speed (opt) is measured. The value is obtained from the sum of the deviation according to (55) for each wheel.

$$\mathrm{PTP}=\frac{\Omega_{max}-\Omega_{opt}}{\Omega_{max}} \tag{55}$$

<u>Integral Pitch Variation (IPV)</u>
Yaw variation (56) does not affect braking distance and maneuverability directly. However, it limits the driver's ability to estimate distances due to the fact that the human brain suffers from a degraded performance in estimation in the presence of excessive yaw, which leads to potential risk situations.

$$\mathrm{IPV}=\int_{t_i}^{t_f}|\theta|dt \tag{56}$$

Table 3 shows the results for the two algorithms studied: threshold control (THR) and the new proposed control (SNN). It includes the obtained KPIs in emergency braking on constant surfaces and surface transitions. This list of conditions has been extracted from Regulation 13 (E/ECE/-TRANS/505/Rev.1/Add.12/Rev.8.3. Regulation No. 13). Consequently, it can be concluded that the controller will behave satisfactorily under any type of road condition or change in the characteristics of the surface.

Table 3. Steady-state KPIs for different road conditions

ROAD	ABSIP THR	ABSIP SNN	PTP THR	PTP SNN	IPV THR	IPV SNN
1	89,5%	**82,5%**	0,20	**0,03**	0,15	0,12
0.7	87,5%	**87,4%**	0,33	**0,11**	0,02	0,06
0.3	**87,4%**	98,1%	0,50	**0,03**	0,01	0,02
1.1→0.58	92,6%	**90,4%**	0,21	**0,18**	0,03	0,08
0.8→0.3	91,3%	**90,5%**	0,59	**0,43**	0,01	0,04
0.3→0.8	**85,3%**	86,4%	0,27	**0,05**	0,02	0,04
0.7 (Rough)	97,7%	**94,0%**	0,48	**0,28**	0,03	0,02
0.3 (Rough)	**95,3%**	103,9%	0,70	**0,22**	0,01	0,01

The performance indicator (ABSIP) provides better results for the proposed SNN-based algorithm. The exception is for the really low grip surfaces where the threshold control (THR) based algorithm performs slightly better. However, PTP KPIs obtained by the SNN algorithm show superior performance of this proposal over its competitor in all cases. The deviation achieved with the SNN algorithm is the lowest in all cases, which ensures a high level of maneuverability of the vehicle, whatever the braking condition. This is of great importance in situations with low adherence since a high deviation increases the possibility of losing control of the vehicle. Therefore, it can be concluded that the SNN algorithm exceeds is competitor and ensures the best response in terms of braking distance and maneuverability. The last KPI that gives information about yaw (IPV) results favorable in both cases with unnoticeable levels of rotation.

The three transitions performed are assessed using also the KPIs associated with the transient response during the jump.

Mean Deceleration (MDj)

This KPI measures the average deceleration obtained during the transition. The deceleration is measured between the start of the transition and one second after it occurs, according to equation (57).

$$\mathrm{MD_{jump}} = \int_{t_{i,j}}^{t_{i,j}+1} a_x \, dt \tag{57}$$

Peak To Peak (PTPj)
The same calculation (55) explained in the previous case is done in this case for the first cycle after the jump.
Maximum Yaw Rate (MYRj)
It quantifies the lateral stability of the change during the transition, as the maximum yaw between the init (i) and the end (e) of the jump (58). This KPI evaluates the influence of a sudden change in adhesion on the yaw angle although this situation does not usually occur as both wheels on each side of the vehicle experience the change in grip at the same time.

$$MYR_{jump} = \max[\dot{\theta}]_{i,jump}^{e,jump} \tag{58}$$

Table 4. Transient KPIs for different road jumps

ROAD	MDj THR	MDj SNN	PTPj THR	PTPj SNN	MYRj THR	MYRj SNN
1.1→0.58	0,56	**0,59**	0,21	**0,18**	0,007	0,028
0.8→0.3	0,24	**0,25**	0,59	**0,43**	0,001	0,001
0.3→0.8	0,63	**0,68**	0,27	**0,05**	0,000	0,000

The results obtained for the transitions show better performance for the proposed SNN-based controller (Table 4). This is due to the ability to adapt to change offered by this controller while the one based on threshold control cannot adapt to change in the same fast manner. Hence, during the transition, it obtains worse deceleration and deviation values. As in steady-state, the obtained value associated with the yaw is reduced, so in both cases the vehicle is maintained stable without large yaw changes.

3.3.Vehicle Experimentation

Once the performance of the proposed control algorithm was evaluated satisfactorily by the conducted simulations, a series of tests in real conditions were carried out using an instrumented vehicle. The proposed algorithm was validated using a test vehicle during a stay at the Swedish University of KTH. The vehicle used was named Research Concept Vehicle (RCVe) in its electric version. The use of this test platform made it possible to implement the developed algorithm using SIMULINK by means of the DSPACE hardware. This device enables the control of the entire vehicle with the ease offered by SIMULINK and its visual programming environment. In addition, during the aforementioned stay, tests were carried out on a track where high and low friction surfaces were available as well as the possibility of performing real surface transitions during braking (Figure 34).

Figure 34. The RCVe (left) and the Arlanda test track with road adhesion transition (right)

Due to the short duration of the stay with only 4 days of track testing, the validation was focused on the control algorithm, which is the main contribution of this thesis. After the adaptation of the code as well as the tuning of the braking system, using only the front axle for the actuation was proposed while the rear axle was used for speed measurement. There were two main reasons for this. The first one was the higher braking capacity of the front axle and the second one was the computational limitation required by the developed algorithm. This meant that the DSPACE hardware required the use of a smaller network and limited its use to only two wheels. It would not be able to run four braking algorithms with the available hardware.
The last consideration to take into account was the speed at which the tests would be carried out. Since it was a vehicle with passengers aimed at performing remote driving tests, its speed was limited to 25 km/h.
Despite the limitations, the stay allowed the correct validation of the implementation of the algorithm in a real system and under varying conditions.

In addition, the algorithm proved its ability to learn and adapt to new situations during its normal operation. Hence, the work developed in this thesis demonstrates its viability for a future application in passenger vehicles.
Three groups of tests were performed on high and low grip surfaces and their transitions between both. Each test group consisted of a series of emergency braking processes. The algorithm initially provided a reduced output since the synaptic forces were quite low. Nevertheless, as the consecutive tests were performed, the network modified its weights and succeeded in increasing and controlling the applied pressure. This behavior was also observed in the simulations carried out in the previous section.
The first group of tests was carried out on a high-adhesion surface. It can be observed how the deceleration increases considerably as the experimentation proceeds (a→ b→ c). As in the simulations (Figure 35), the pressure during experimentation (Figure 36) rose for each iteration, thus reducing the braking distance as the slip increased throughout the test. The neural network did not stop controlling the braking, even in experimentation (Figure 37).). This highlights the importance of the prefixed neural structure that provides the necessary robustness for online learning.

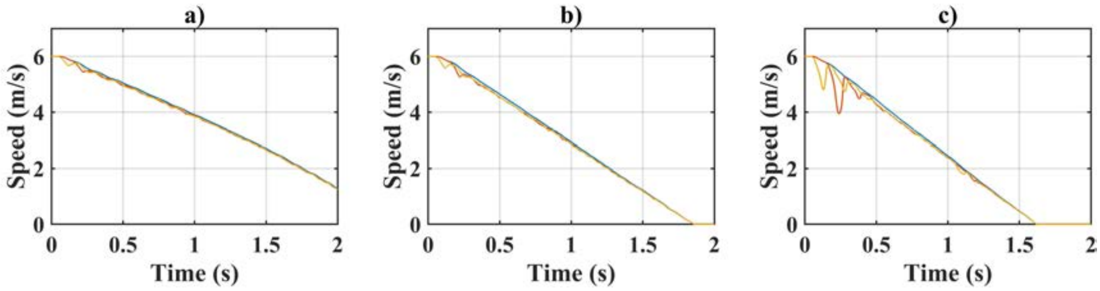

Figure 35. Vehicle speeds under supervised learning process (Simulation) (a)First iteration, b)mid-learning, c)completed)

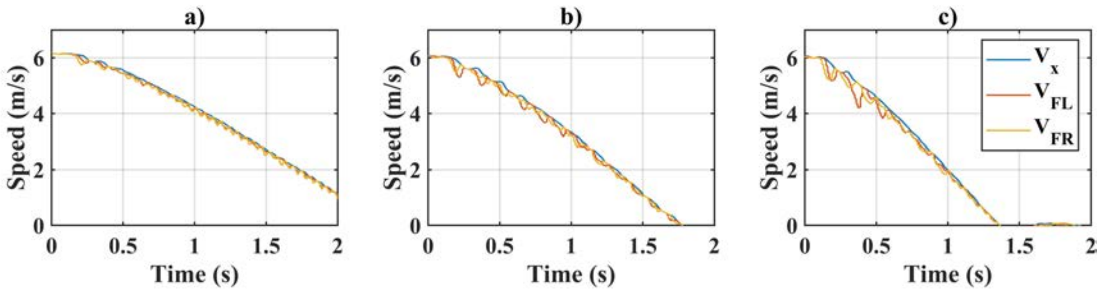

Figure 36. Vehicle speeds under supervised learning process (Experimentation) (a)First iteration, b)mid-learning, c)completed)

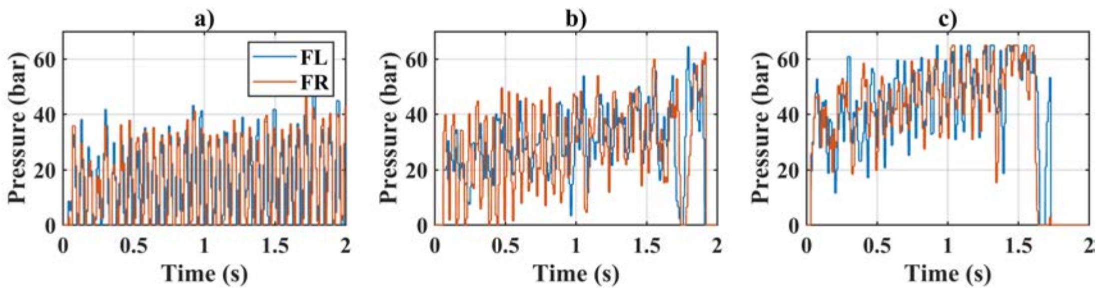

Figure 37. Braking torque under supervised learning process (Experimentation) (a)First iteration, b)mid-learning, c)completed)

Results after training on the remaining surfaces are shown in Figure 38 where the following tests were conducted: low adhesion surface, high-to-low adhesion transition at 4.5m/s, low-to-high adhesion jump at 4.5m/s and, to conclude, braking with a different adherence in each tire (left tire low adhesion, right tire high adhesion).

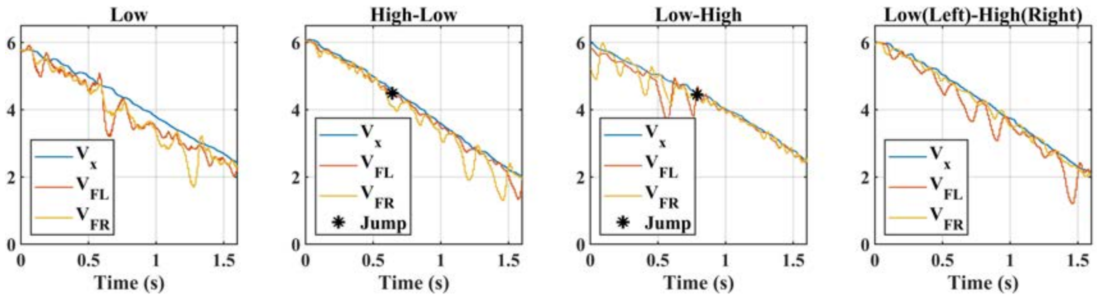

Figure 38. Vehicle speeds after training for different situations (Experimentation)

As it can be observed, the algorithm deals with the surface transition without large oscillations and provides a reduced braking distance as previously presented in the simulations.

Table 5 below shows a summary of the results. A comparison has been made between the proposed algorithm based on SNN and the threshold control-based one. The obtained results indicate that the proposed algorithm obtains a better deceleration in all situations. The difference is even greater than in simulations since the threshold control algorithm is not able to adjust to real behavior. This is due to the low speed (6m/s) of the tests, making control even harder as adhesion increases.

Table 5. Steady-state KPIs comparison between simulation and experimentation (6 m/s)

ROAD	Simulation				Experimentation			
	ABSIP THR	**ABSIP SNN**	**PTP THR**	**PTP SNN**	**ABSIP THR**	**ABSIP SNN**	**PTP THR**	**PTP SNN**
0.9 (High)	96.5%	**91.3%**	0,17	**0,15**	99.12%	**97.5%**	0,63	**0,10**
0.6 (Low)	95.67%	**89.08%**	0.81	**0.27**	98.56	**94.91%**	0,74	**0,12**

These tests conclude the work carried out in this thesis. It started with the development of the equations and algorithm based on SNN. Next, this type of neural networks was used for control applications. Subsequently, a learning strategy was required to improve the performance of the algorithm in all conditions. Once the response of the algorithm was considered satisfactory, its application to vehicle control systems was tackled. Simulations and real tests have demonstrated the superior performance, robustness and stability of the proposed approach. This work covers the basic methodology and validation by simulation and experimentation.

4. Conclusions

This work has been devoted to designing controllers based on spiking neural networks to improve the performance of vehicle safety systems. In addition, a learning strategy capable of updating controller parameters, depending on driving conditions, has also been developed. The proposed algorithm has been tested in simulations and real testing, which has confirmed the viability and robustness of this approach and its superior performance over selected competitors.

Thus, this thesis has made it possible to establish a new strategy to develop biologically-based controllers for vehicular systems that will contribute to increasing the safety of road users. Vehicular and neural control were initially studied separately to finally integrate them and validate their performance through simulation and real tests.

Next, the main contributions of this work are highlighted:

- A control scheme used has been simulated and validated using two and four-wheeled experimental vehicles. The estimation and identification of parameters, using an extended Kalman filter and a classification neural network respectively, have demonstrated their ability to detect the adherence conditions as well as the level of tire slippage.

- Based on a bio-inspired reflex arc structure, a controller capable of coping with systems with highly nonlinear behavior has been developed. Its simplified structure makes its execution in real-time possible, which allows its integration into embedded control systems.

- A slip control algorithm, based on spiking neural networks, has been proposed. This control adapts to the varying conditions of tire-road contact dynamics. In addition, by programming a neural plasticity strategy, the synaptic strength is modified with a supervised learning method, which contributes to minimizing the control error.

- The modulation of dopamine as well as the use of different STDP rules allows the tuning of the synaptic strengths of the neural network. The learning algorithm reduces the error made by the network in a reduced number of iterations in control and classification applications.

- The combination of classification and control in a single neural network demonstrates the capability of performing full neural control using the proposed neuron model as a single resource. Learning in this manner makes use of the inputs and outputs of both networks efficiently, just as in biological systems.

- Results obtained in simulations and experimentations have proved the effectiveness of the proposed algorithm versus other controllers proposed in literature. The ability to learn and adapt to unknown conditions during real tests is remarkable.

- The adaptation capability of the controller, which allows updating the parameters of the networks through the designed learning strategy, provides a further advantage of this proposal over its competitors in case of deterioration or replacement of a tire. Commercial algorithms lack this learning or updating capacity since they do not know the dynamics of the tire used. Thus, conventional approaches cannot offer an optimal response in emergency braking in all conditions.

5. Recommendations for future work

The development of the proposed controller provides an innovative line of research with a wide range of possible applications in engineering problems. In the automotive field, its potential can rapidly be scaled up for the control of a great number of safety systems.

The extension of the algorithm to include lateral dynamics will allow performing stability control for four-wheel vehicles without requiring major changes of the control structure. Moreover, the updating of the structure to adapt inputs and outputs to the variables used by other vehicle controllers will make its extension to other applications possible.

Control algorithms such as torque vectoring, brake blending, stability control or steering-by-wire resort to similar structures and would, consequently, benefit from the work done in this thesis. Other high-level control algorithms, such as advanced driver-assistance systems (ADAS) and those needed for a self-driving car, are clear targets for an extension of the algorithm proposed in this thesis.

Furthermore, the possibilities of improvement and extension of the approach are numerous. The study of more complex structures with more variable inputs presents a challenge in the establishment of neural connections. Likewise, the study of different neural models and their temporal response enables the ability to establish more complex relationships such as temporal dependence, for example, without the need for recurrent structures.

A larger structure would also allow identification using the proposed neuronal system, without requiring the use of an extended Kalman filter or any other estimation algorithm. This opens the possibility of a more complex learning and control algorithm since it would have direct access to the required information for control coded with spikes. It also raises the feasibility of adding learning to classification and identification, for which it would be necessary to set a fixed structure to ensure stability in the obtained response.

The use of neuromorphic hardware also broadens the possibility of using more complex structures with the challenge of integrating them into real-time systems. Therefore, it is hoped that this is only the beginning of a research line that is yet to be explored.

The simulation of the behavior of biological systems is another possible line of research in the future. Comparing the behavioral response of an arm by contrasting the results with real ones opens up the possibility of simulating the behavior of biological systems. This allows validating control schemes such as the one based on the equilibrium hypothesis as well as predicting future behavior.

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Part II: Appended papers

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1.Paper A

2.Paper B

3.Paper C

4.Paper D