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Spiking control: bioinspired solution to address nonlinearities in control systems

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Resumen

La ingeniería neuromórfica proporciona mecanismos de inspiración biológica para procesar información de manera eficiente, ofreciendo nuevas oportunidades para sistemas de control que operan bajo dinámicas no lineales y dependientes del estado. En este contexto, el control pulsátil o *spiking control* (SC), basado en modulación por eventos tipo *spiking*, codifica las señales de control en trenes de pulsos que se adaptan de forma natural a la dinámica del sistema, reducen el consumo de energía y reducen los efectos de las no linealidades. Este trabajo resume las principales contribuciones de los autores al SC (también conocido como *neuromorphic control*) mediante varios ejemplos de aplicación que demuestran su potencial para mejorar la eficiencia en escenarios de control no lineal.

Palabras clave: Control pulsátil, Ingeniería neuromórfica, Sistemas de control, Aplicaciones, Neurona, PFM, Estrategias bioinspiradas, Modulación por pulsos, Motor DC, Válvula solenoide

Spiking control: bioinspired solution to address nonlinearities in control systems

Abstract

Neuromorphic engineering provides biologically inspired mechanisms for processing information efficiently, offering new opportunities for control systems operating under nonlinear and state-dependent dynamics. In this context, spiking control (SC), based on spiking, event-driven modulation, encodes control signals into pulse trains that naturally adapt to system dynamics, reduce energy consumption, and directly shape input nonlinearities. This paper reviews the authors' main contributions to SC (also known as neuromorphic control) through several application examples that demonstrate its potential for improving efficiency in nonlinear control scenarios.

Keywords: Spiking control, Neuromorphic engineering, Control systems, Applications, Neuron, PFM, Bionspired strategies, Pulse modulation, DC motor, Solenoid valve.

1. Introduction

Neuromorphic engineering draws inspiration from the principles of nervous systems to develop more efficient hardware and software architectures. Carver Mead, who argued that the brain could outperform digital technology by several orders of magnitude, advocated for analog silicon systems capable of emulating neural computation. Since then, neuromorphic engineering has advanced primarily through low-power microelectronics that seek to replicate neural topology and processing. Although standard neural networks were initially developed as a parallel field rooted in mathematics and statistics, these paths have merged through Spiking Neural Networks (SNNs), combining brain-inspired processing with modern algorithmic success.

Among the many concepts emerging from neuromorphic research, this work is motivated by the way biological neurons transmit information through pulse trains. Pulse-frequency modulation (PFM) was originally formulated as an abstraction of neural communication in physiological control systems, and

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it has since demonstrated practical benefits. For example, PFM can improve power efficiency in switching regulators, especially at low load, because power losses scale with the number of switching events. It is also inherently robust to noise, as information is encoded in pulse timing rather than amplitude, and it provides advantages in actuator precision. Notably, PFM naturally handles static friction in DC motors by allowing the energy of each pulse to be tuned to overcome static friction. Several commercial converters now combine PFM and pulse-width modulation (PWM) to exploit the strengths of both.

However, conventional pulse-width modulation (PWM) schemes, which rely on fixed switching frequency, are inherently ill-suited to systems exhibiting nonlinear, state-dependent dynamics. Attaining satisfactory control performance under such conditions generally necessitates the introduction of additional compensation mechanisms. Dead-zone effects are frequently treated by incorporating feedforward offsets; nevertheless, this strategy alone is insufficient to guarantee consistent behavior, as the resulting system response remains highly sensitive to the current operating state. To alleviate this dependence, more advanced feedback architectures —most notably adaptive and robust control frameworks— have been proposed and investigated.

The advantages of using a bioinspired solution is that the efficiency and robustness attributed to the biological process can be expected to appear as a positive side effect.

In control systems, the idea of spiking control (SC) has recently gained traction as a neuron-inspired modulation technique that encodes the output of a main controller into pulses. SC is inherently a form of spiking, event-based control, in which actuation is triggered only when required by the system dynamics, leading to asynchronous, state-dependent switching that can reduce energy consumption and directly shape input nonlinearities (Sepulchre, 2022; Schmetterling et al., 2024). Recent studies show that spiking controllers can exploit the intrinsic dynamics of robotic bodies, pointing toward a new class of efficient and robust control strategies (Arbelaiz et al., 2025a; Yoshioka et al., 2024).

The term neuromorphic control (NC) is also employed in the literature as a broader concept that may encompass additional forms of bioinspired strategies. In the present work, however, the term SC has been adopted preferentially in order to emphasize the specific mechanism by which the control signal is transmitted. It should be explicitly noted that this study focuses on providing experimental evidence and establishing design criteria for addressing nonlinearities, rather than conducting a formal stability analysis.

The remainder of this paper is organized as follows. Section 2 introduces the fundamentals of silicon neurons. Section 3 presents the principles of spiking control. Section 4 summarizes the authors' main contributions to this research area and illustrates them through several application examples. Finally, Section 5 summarizes the main conclusions.

2. Fundamentals of silicon neurons

The current landscape of neuronal modeling presents a spectrum of abstractions. First, mathematical models based on neuron structure provide high biological accuracy but entail significant computational overhead. Second, abstract input-output descriptions, such as integral PFM (IPFM), focus on functional signaling by simplifying complex neuronal dynamics. Lastly, analog implementations constitute a hardware-centric approach, leveraging the intrinsic physical properties of electronic devices to achieve energy-efficient neuromorphic computing. However, the boundaries between these categories are often blurred, as many practical models frequently overlap or integrate elements from different approaches to balance biological realism with technical constraints.

The realization of these diverse paradigms is encapsulated into the concept of silicon neurons. Whether implemented as analog, digital, or hybrid circuits, they function as the core building blocks for neuromorphic architectures. There are many types of silicon neurons that vary in complexity depending on the application. In particular, biophysically realistic models that emulate the detailed internal dynamics of the neuron can be found in the literature, such as the Hodgkin-Huxley model as well as basic circuits that attempt to directly mimic the spike-like output of real neurons, such as integrate-and-fire (I&F) circuits. For convenience, those most closely related to our developments are described below:

- *Leaky integrate-and-fire neuron*: early designs of silicon neurons were used to mimic the firing frequency of real neurons by simply using a resistor-capacitor (RC) circuit, leading to the concept of I&F neuron models:

$$C\frac{dV(t)}{dt} + \frac{V(t)}{R} = i(t) \tag{1}$$

  where C is the neuron membrane capacitance, R is the membrane resistance, $V(t)$ is the membrane voltage and $i(t)$, the input current (Abbott, 1999).

- *Fractional-order integrate-and-fire neuron*: introduces the fractional order in the derivative to model the spike frequency variation in response to constant stimuli, also known as adaptation or accommodation, observed in some types of real neurons:

$$C\frac{d^{\alpha}V(t)}{dt^{\alpha}} = i(t) \tag{2}$$

  where $\alpha \in (0, 1)$ is the fractional order (Teka et al., 2014).

- *Hodgkin-Huxley neuron*: is considered the most realistic and precise model of a biological neuron, given by:

$$C\frac{dV(t)}{dt} = \sum_i g_i(V(t))(V(t) - V_i) + i(t) \tag{3}$$

  where V_i and g_i are the reversal potentials and the conductances, respectively, of the potassium and sodium channels, as well as the leaky terms (Gerstner et al., 2014). The complex neuron dynamics are well represented, such as bifurcations and accommodation. Although being the most accurate becomes impractical for control purposes due to its high-dimensional nonlinearities. In engineering, approximations of this expression are preferred when bifurcations are helpful, such as the FitzHugh-Nagumo model (Arbelaiz et al., 2025b).

- *Axon-Hillock neuron*: represents one of the most compact implementations of a self-resetting neuron. It is typically realized using two capacitors and a small number of transistors, and its dynamical behavior can be described in terms of two principal phases, conventionally referred to as depolarization and repolarization (Mead, 1989). During depolarization the voltage evolves as:

$$\frac{dV(t)}{dt} = \frac{i(t)}{C_1 + C_2} \tag{4}$$

where C_1 and C_2 are the capacitances. During repolarization:

$$\frac{dV(t)}{dt} = \frac{-I_{dis} + i(t)}{C_1 + C_2} \approx \frac{-I_{dis}}{C_1 + C_2} \tag{5}$$

where I_{dis} is a discharging current.

3. Spiking control

The strategy exploits neuron dynamics to counteract actuator nonlinearities. It uses a main controller (e.g., a classical proportional-integral PI controller) in cascade with a neuron-like element that converts the control signal into a two-state signal, as shown in Figure 1.

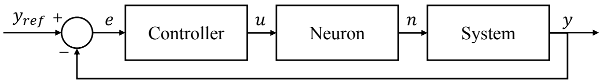

Figure 1: Spiking control closed loop scheme.

The integral PFM (IPFM) neuron is described by the following two equations (Jones et al., 1961; Li and Jones, 1963). The first, describes the integration of the input up to a threshold:

$$s(t) = \int_{t_{k-1}}^{t} u(t)dt < K_{ti} \tag{6}$$

where $u(t)$ is the control signal, $s(t)$ is the integral (similar to membrane voltage in previous models), K_{ti} is the threshold, and t_k is the k-th time $s(t)$ crosses the value K_{ti} ($s(t_k) = K_{ti}$). At each t_k instant, the integral is reset:

$$s(t_k^+) \leftarrow 0 \tag{7}$$

The second, describes the output which is a pulse train:

$$n(t) = A\sum_{k=1}^{N}[H(t - t_k) - H(t - t_k - t_h)] \tag{8}$$

where A is the pulse amplitude, t_h is the pulse width, N is the number of pulses during the experiment.

The three main parameters of the neuron are: the pulse amplitude A, the pulse width, t_h, and the threshold, K_{ti}. Parameters A and t_h determine the power delivered by each pulse, and hence, the intensity of the response every time the neuron internal variable, $s(t)$, crosses the threshold. The threshold determines the firing frequency by:

$$f = \frac{\bar{u}_k}{K_{ti}} \tag{9}$$

where $\bar{u}_k$ is the average of input u in $[t_{k-1}, t_k]$.

For unitary modulation the average of the control signal and the average of the pulse train signal must be equal: $\bar{u}_k = \bar{n}_k$. Then, the threshold value must be $K_{ti} = At_h$. For any other value of the threshold, the neuron introduces a gain, denoted as G: if $K_{ti} = GAt_h$, then $\bar{n}_k = \bar{u}_k$/G.

The usual utility of a pulse modulator is to encode the control signal into a two state level. The output signal is aimed to be a representation of the input with sufficient accuracy to translate the capabilities of the controller into the two state domain, such as digital. In our work, we explore that it has an additional use, which is the linearization of the average system response with regard to controller output signal. It is achieved by exploiting the nonlinearities of the neuron.

Based on the previous rationale, the spiking controller is designed following a two-step procedure. In order to treat as the neuron and the main controller as decoupled subsystems and design them separately, the neuron dynamics is intentionally made faster than that of the desired closed loop dynamics. First, the neuron parameters are selected to counteract system nonlinearities. Then, the linear controller is tuned to regulate the resulting neuron–plant combination, which can be regarded as an approximately linear system.

4. Application examples

This section reviews several application examples that illustrate the breadth and potential of NC in practical scenarios. First, NC is applied to the low-velocity control of DC motors, where pulse-based actuation naturally compensates static friction. Second, its use in soft pneumatic systems is examined, enabling improved pressure regulation in solenoid valves. Third, an event-based anti-windup strategy is presented, demonstrating how spiking mechanisms can enhance nonlinear compensation in saturated systems. Finally, applications within a fractional-order framework are discussed, including the introduction of fractional dynamics in both the neuron and the main controller, as well as an analog hardware implementation.

4.1. Control of DC motors at low velocities

The analog controller requires a relatively high reference signal to overcome the static friction of the motor. When the reference velocity is reduced, the system tends to stick. In contrast, each pulse in the pulse servo provides enough energy for the motor to overcome static friction (De Weerth et al., 1990).

The DC motor can be modeled as a linear system with static friction, acting like a dead-zone at zero velocity. To surpass dead-zone, the actuation signal must surpass a threshold, and, due to the transients of motor states, there is also a minimum time required under such excitation. We can design neurons to produce pulses that satisfy both conditions, such that each pulse is sufficient to surpass the dead-zone. For a detailed explanation of the theoretical aspects and tuning procedure, readers are referred to (Serrano-Balbontín et al., 2025a).

Figure 2 shows the application of spiking control to a DC motor that runs at low velocities. In Figure 2 (a) The closed-loop diagram is presented, and in Figure 2 (b) the position response and the neuron output (n) are presented. The effect of the friction almost vanishes, while the transient is similar to that of linear systems.

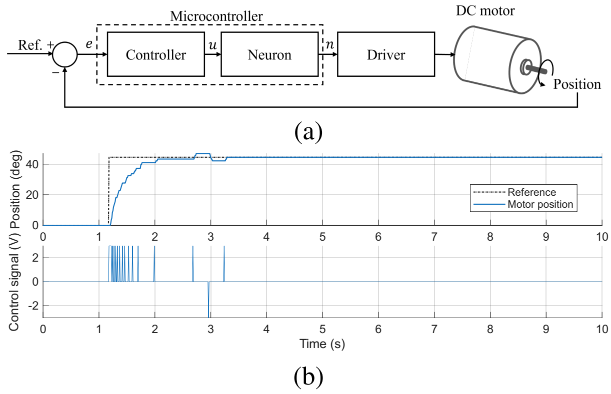

Figure 2: Example of DC motor position control at low velocities: (a) closed loop scheme (b) system response under static friction.

4.2. Control of solenoid valves in soft pneumatic systems

On/off solenoid valves are electromechanical binary devices that allow to alternate between air flow paths.

Analogously to DC motors, the electromechanical components of a solenoid valve require a minimum excitation level to overcome frictional effects and opposing pressure forces. However, the dynamic behavior of solenoid valves is more complex. In particular, there exists a minimum deactivation threshold required to restore the initial position, which gives rise to a saturation phenomenon. Moreover, in contrast to DC motors, even when dead-zone and saturation effects are compensated for or eliminated, the system remains strongly nonlinear.

To effectively address the nonlinearities, both excitation and recovery times are ensured by encoding the control signal through a neuron-based representation, thereby eliminating dead-zone and saturation effects. Moreover, the neuronal encoding mitigates the remaining nonlinear behaviors. In closed-loop operation, the overall system performance becomes more consistent. All information about this application can be found in (Serrano-Balbontín et al., 2025b,c).

Figure 3 shows the application of the spiking control strategy to the pressurization process of a soft pneumatic actuator (SPA) driven by a solenoid valve. Figure 3 (a) the schematic is depicted, and in Figure 3 (b) the response of the pressure inside a SPA that is controlled by a solenoid valve is shown. The nonlinearities are addressed such that a PI controller is sufficient to control the pressure while consistently satisfying the prescribed control specifications.

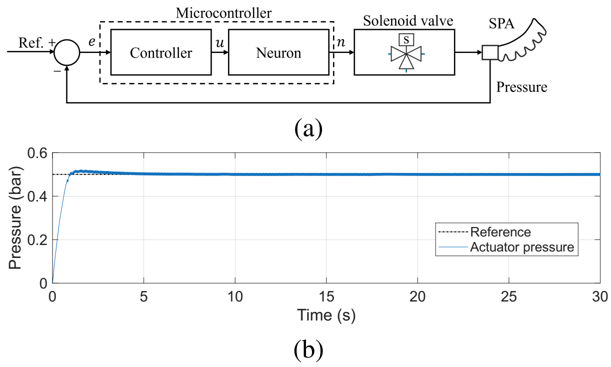

Figure 3: Example of soft actuator pressure under spiking control: (a) closed loop scheme (b) system response under static friction.

4.3. Event-based anti-windup strategy

A major source of performance degradation in practical PID controllers is integral windup, which arises when the controller output saturates due to actuator limits, thereby inducing excessive overshoot and prolonged settling times. A conventional design procedure consists of first tuning the controller under the assumption of linear actuators, and subsequently augmenting the classical proportional-integral-derivative (PID) algorithm with an anti-windup mechanism to handle integrator saturation. In the proposed approach, a neuron is employed to encode the saturation error-defined as the difference between the controller output and the actuator output-into a sequence of pulses, such that the back-calculation is activated intermittently in accordance with the magnitude of this error, as shown in Figure 4.

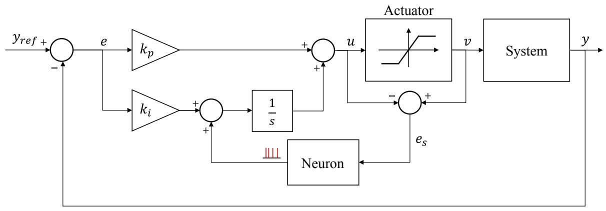

Figure 4: Spiking back-calculation anti-windup strategy applied to a PI controller.

It has been observed that the incorporation of neurons into the anti-windup loop, with an appropriate selection of their parameters, yields performance comparable to that of the standard back-calculation algorithm. Moreover, when the amplitude or width of the neuron-generated pulses is increased, the number of time instants at which the controller signal must be recomputed is significantly reduced.

This is a step towards using a control scheme that simultaneously encoding the controller signal in neurons combined with a back-calculation strategy to design a spiking controller that handles friction-limited systems with saturation-constrained actuators.

Figure 5 shows the effect of varying t_h on the output. For narrow pulses, the output closely matches the continuous case, and the neuron acts as a good modulator with little distortion. As t_h increases while keeping the neuron gain constant, the pulses generally reduce output smoothness. For larger values, such as $t_h = 1$ s, the output leaves the saturation path earlier than in previous cases, producing a backward movement not seen in the traditional back-calculation structure. Note that the variation of parameter A has similar effects.

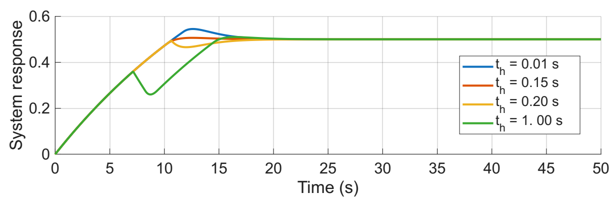

Figure 5: System response for various pulse intensities under spiking back-calculation.

For a more detailed treatment, the reader is referred to (Serrano-Balbontín et al., 2024b).

4.4. Fractional-order approach

Fractional-order control works with control systems that use derivatives and integrals of non-integer order, which considerably broadens the horizons of control engineering. The convenience of applying fractional-order control (FOC) in different control systems has been widely demonstrated in e.g. (Feliu-Talegon et al., 2019; Hosseinnia et al., 2014; Monje et al., 2010, 2008).

The authors' early contributions within this framework established the foundations of fractional neuromorphic control (FNC) by combining pulse-based neuromorphic modulation with FOC to address nonlinear and friction-dominated systems (Serrano-Balbontín et al., 2023a). In particular, a fractional-order controller generates a continuous control signal that is subsequently encoded into spike trains by silicon neurons, yielding an event-driven actuation strategy capable of overcoming static friction while preserving robustness against load variations. Simulation results on low-speed DC motor control demonstrate that FNC maintains a nearly constant overshoot under significant parameter changes, outperforming classical integer-order controllers in scenarios dominated by nonlinear friction effects.

Building on this concept, an analog implementation of FNC was proposed in (Serrano et al., 2023) and systematically analyzed. The implementation of NC using analogue circuits also offers the ability to create regulators with few components and low energy (De Weerth et al., 1990). In this context, the spiking controller is realized using analog fractional-order operators and Axon-Hillock-type neurons, providing a fully asynchronous, low-power solution suitable for hardware implementation. A detailed design methodology is presented, linking control specifications to neuron parameters such as pulse amplitude, pulse width, and inter-spike interval scaling. Physical modeling using Simscape validates the analog realization, showing close agreement with ideal fractional-order behavior and confirming the feasibility of implementing spiking control strategies in continuous-time analog hardware.

Complementarily, the hardware feasibility and flexibility of neuromorphic and fractional concepts were further explored in (Serrano-Balbontín et al., 2024a) through a field-programmable analog array (FPAA) implementation of silicon neurons with fractional dynamics. An FPAA is an integrated circuit using switched capacitor technology that provides the ability to configure an analog signal processing system. This work demonstrates how neuromorphic pulse-based modulation can be rapidly prototyped using reconfigurable analog hardware, implementing both classical Axon-Hillock neurons and a true pulse-frequency modulation neuron that preserves correct frequency encoding even for non-negligible pulse widths. Fractional dynamics is incorporated at block-diagram level by combining integer-order neuron models with fractional-order operators, enabling the reproduction of spike-frequency adaptation under constant or periodic inputs. The FPAA-based results highlight the suitability of this platform for validating low-complexity neuromorphic circuits with fractional memory effects and bridging the gap between conceptual NC designs and practical hardware realizations.

A further step was taken in (Serrano-Balbontín et al., 2023b) by introducing fractional-order integrate-and-fire (FO I&F) neurons that inherently exhibit adaptation, a key feature observed in biological neurons. An analog realization of an FO I&F neuron with reset was developed, overcoming the classical difficulty of preserving fractional memory under reset conditions. By combining a fractional derivative with an integer-order integrator, the proposed neuron reproduces spike-frequency adaptation while remaining compatible with closed-loop control. When integrated into NC schemes, fractional neurons reduce steady-state chattering without degrading tracking performance, highlighting their potential for improving efficiency and smoothness in spiking control systems.

5. Conclusions

Our research approach commences with the election of the most simple, yet powerful model of neuron (IPFM) to study the problem in its simpler form. Once the effect of this type of information handling is fully understood we proceed with the addition of further realistic dynamics of the neuron in order to explore their additional advantages: leaky as noise filtering, fractional as input relevancy.

Overall, these works demonstrate that spiking control (SC), particularly when enriched with fractional-order dynamics at both the controller and neuron level, constitutes a powerful bioinspired solution to cope with nonlinearities, friction, and robustness requirements in control systems. Beyond performance improvements, the proposed strategies emphasize hardware efficiency and implementability, ranging from fully analog realizations to reconfigurable FPAA-based prototypes that enable rapid validation of neuromorphic and fractional concepts. In particular, FPAA implementations show how silicon neurons with fractional dynamics and spike-frequency adaptation can be realized with low complexity, providing an intermediate step between theoretical designs and custom analog VLSI solutions. Together, these contributions highlight spiking control as a flexible, energy-efficient, and hardware-oriented control paradigm, well suited for future embedded and resource-constrained applications where nonlinearities and efficiency are critical.

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