Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Examining the Software Implementation of Pain Sensation on the Fpga Board Using the Neuromorphic Concept

Somayeh velaei[1], Behzad Yasrebi[2]

1- Department of Biomedicl Engineering, Islamic Azad University, Tabriz branch, Tabriz,, Iran

2-Department of Biomedicl Engineering, Islamic Azad University, Tabriz branch, Tabriz,, Iran

Abstract: *Background: The sense of touch plays an important role in our interactions with the surrounding environment. Mechanical arms, robots and neural prostheses will function better with a sense of touch. Microneurography studies in humans have shown that primary afferent neurons such as receptors Fingertip mechanics play an important role in encoding and discriminating different types of stimuli using spike train patterns.Objective: To investigate the software implementation of pain sensation on FPGA board using the concept.Research method: a laboratory method for simulating the responses of the slow matching receptor. It has been applied to force stimulation by considering the spiking behavior. In fact, to detect the force, Izhikevich sensor data and spiking characteristics were used. The sensor's analog signal was applied as an input current to the neuron model in order to obtain spike trains. The features of the spike trains were extracted by rate coding and spike timing coding.) and kNN (k-nearest neighbor) were given to classify all types of forces. Results: The highest accuracy of the rate coding feature class with 100% accuracy, (ISI CV) Inter-spike intravel coefficient of variation with 81.18% accuracy and (VPD) Victor-purpura distance with 82% accuracy was obtained. Also, rate coding and time coding were also calculated using spike trains resulting from mutual information contact force.Results: Sending information by rate coding method is more than spike timing coding in stimulating the Merkel receptor. Also, with increasing power, the firing rate of the Merkel receptor also increases.*

Keywords*: pain sensation, EEG signal, neuromorphic concept*

1. Introduction

Pain is a complex experience that includes many aspects including physiological, behavioral and psychological factors. Pain causes the release of chemicals that activate the nervous system to warn the body of a real and potential injury, and since it is a multidimensional experience, its assessment requires multidimensional measurement tools. Suffering and disability caused by pain reduces the quality of life in many people, therefore pain grading and, accordingly, pain control is one of the important goals in the treatment of diseases and is of great importance to doctors. Currently, pain measurement scales that depend on a person's thinking, such as visual analog scale, verbal rating scale, and numerical rating scale, are used in clinical evaluation. In addition to the above, changes in blood pressure, electrical conductivity of the skin and other physiological parameters are used to measure the level of pain in patients.

In addition to the above, changes in blood pressure, electrical conductivity of the skin and other physiological parameters are used to measure the level of pain in patients.

In a brain-computer interface system, there is a possibility of artifacts such as blinking and body movements during signal recording, which reduce the quality of the recorded signal and, as a result, cause problems in the feature extraction stage. Therefore, using an algorithm such as independent component analysis, which is one of the most important algorithms in the preprocessing of biomedical signals, can effectively remove artifacts.

Neuromorphic systems refer to types of computers and systems that are inspired by the human brain, and these systems are compared to the pervasive computer architecture of von Neumann and are very similar to neurons and synapses. Synthetics that can be used to model neuroscience theory as well as challenge machine learning problems are relevant. This technology is creating a brain-like ability to learn and adapt, but it is one of the most important technical challenges. Designing a machine that can process information faster than a human has been a driving force in decimal computing, and the von Neumann architecture has become the clear standard for such a machine. However, the comparison of this architecture with the prominent part of the human brain shows significant differences in the organizational structure and required power and processing capability between the two. This has led to a natural question about the possibility of creating secondary architectures based on neuroscience that are favorable to a biological brain, neuromorphic computing in recent years as a complementary architecture to phonological systems. New ones have appeared.

To achieve this goal, the following sub-goals have been completed.

1. In this research, applying tactile stimulation of neurons.

2.In this research, three characteristics of spikes, the number of spikes in a certain time period ,Victor-purpura distance (VPD) and Inter spike interval (ISI) variation coefficient were obtained and these features were used to classify forces in rate coding and time coding.

3.In this research, revealing the amount of force applied to the sensor, hardware implementation of Meissner and Merkel receivers on Field Programmable Gate Array (FPGA).

2. problem statement

As a highly advanced system in nature, the human brain has massive parallelism, strong fault tolerance, self-consistency and self-learning ability in information processing, which enables it to effectively perform complex tasks such as summary learning, reasoning, generalization. A biological neural network consisting of approximately 1011 neurons and 1015 synapses is responsible for perceptual transmission and processing of environmental information [1].

Brain waves are recorded by electroencephalography by brain wave recording devices, which are usually used for recording brain waves due to their high time accuracy, low cost, and ease of use.EEG electrodes are placed on the surface of the scalp and record the electric field resulting from the activity of neurons. To examine how different brain regions connect during pain, extracellular electrophysiology and EEG provide the best temporal resolution. Field potentials resulting from collective activities of local neurons can reveal the current state of the recorded area. And the synchronization between the field potentials created by two different regions can show the functional relationship between them [2].

Neuromorphic computers are a non-von Neumann computing technology in which the computer's architecture and functionality are inspired by biological brains.

Instead of normal computers that have processing and memory components, neuromorphic computers are composed of neurons and synapses [3]. Neuromorphic computing systems aim to process information in a similar way to the human brain. Instead of a typical von Neumann computer, a neuromorphic system generally relies on a neural network, where the memory and processing elements are tightly integrated into the same hardware [4]. Neuromorphic computing uses computing memories that can process data through physical laws within the device or circuit.

Figure (1) shows the structure of the neuron.

This network works like a function that receives input according to the number of input neurons and outputs according to the number of output neurons. Neurons are composed of soma, axon and dendrite. Soma is responsible for receiving and integrating input information and transmitting it. Dendrites are short and branched and extend directly from the soma to form a dendritic shape that is used to receive impulses from other nerve axons and transmit them to the soma.

The axon is narrow and has almost no branches and receives and transmits external stimuli. Most neurons receive signals through dendrites and somatic cells, then transmit signals through axons, and finally transmit them to other neurons through synapses at the end of axons [5].

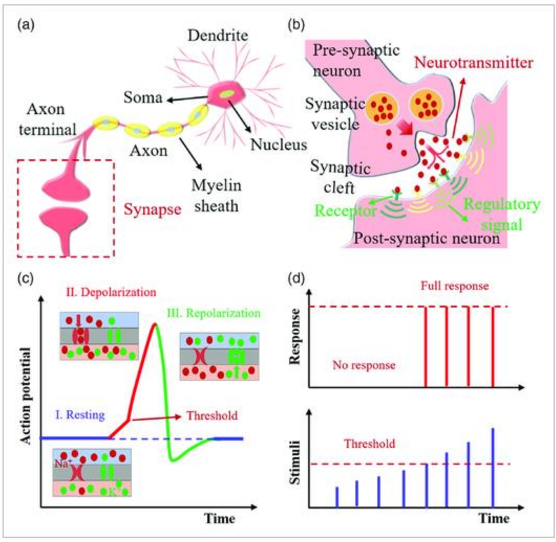

Figure 1: Neuron components [13].

The components of a multilayer neural network include layers and weights. Layers are formed based on the interconnected connection of several neurons that connect the input set to the output. Each two layers of a network are connected by means of weights and connections [13]. Synapses, which are the basic units of the nervous system, are distributed and connected to all types of neurons in parallel, and can modulate and remember the activity of related neurons by changing the strength of connection with neurons, that is, synaptic weight. . Neurons are excited from the postsynaptic membrane, and when the membrane potential exceeds a certain threshold, neurons respond to activation and complete the transmission and processing of physiological signals [6].

A basic neuromorphic unit has several synapses and a neuron block. This unit imitates the biological nerve cell in which synapses receive synaptic pulses from other connected neurons and convert them into currents based on their synaptic strength, and neuron block , the collection of time space performs the pulse impulses and produces the output pulses like the function of the soma. In addition, dendrite and axon blocks are implemented using internal connection circuits that model pulse signal propagation in nerve fibers. An example of a biological nerve cell is shown in the figure (2) [7].

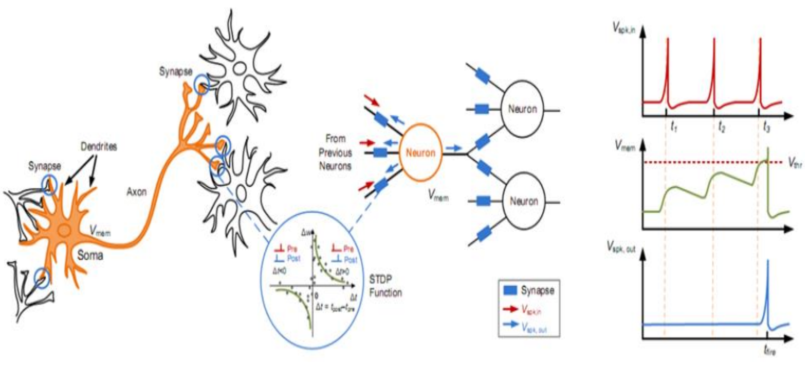

Figure 2 : A biological neuron cell example[15].

The neural network is inspired by the tangled structure of the human brain. Billions of nerve cells form a biological nerve network in the human brain through the connections they have with each other (synapses) [7].

The neuron integrates these incoming currents to change the voltage of the shell or membrane; When the membrane exceeds the threshold excitation value, the neuron is excited and sends a pulse to the presynaptic and postsynaptic neurons [8]. Similar to a biological synapse, the conduction of a stable memory can be gradually changed by controlling the potential of its two ends. Synaptic weight is adjusted based on the relative time of pre-synaptic and post-synaptic excitation of neurons [9]. Repeated arrival of the presynaptic pulse before the postsynaptic pulse leads to a larger synaptic weight; While repeated arrival of the pulse after the post-synaptic pulses leads to a smaller synaptic weight. By hierarchically connecting several neuronal and synaptic blocks, larger signal processing networks can be created [10]. One possible way to determine the spectral components in the input analog signal for neuromorphic computing is shown in the figure (3).

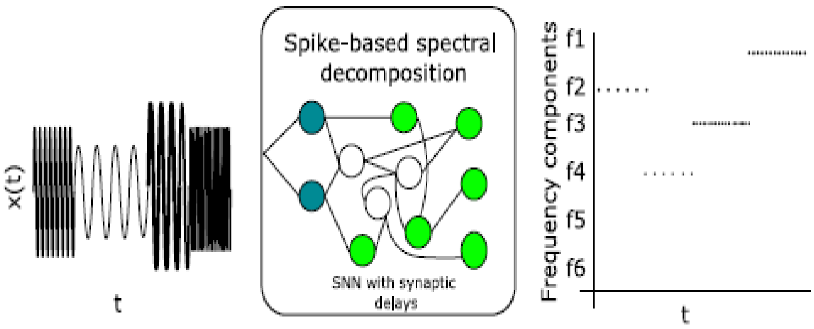

Figure 3: Determination of spectral components in the input analog signal for neuromorphic computing [19].

Here, the light green circles represent the output neurons, each corresponding to a different frequency.The spike rate can be considered as a representation of the power spectral density of each component in the signal [11].The system of neurons and synapses that transmit these electrical impulses is known as a spiking neural network.This system measures the changes in the analog signal.In traditional neural networks, digital signals are used in a very small amount [12].

Stochastic spiking behavior is observed in biological neural systems, and neuromorphic computing hardware often has corresponding stochastic components.The abundance of PRNGs allows the updating of random neurons, usually in the membrane potential or in the integration of new spikes.These neuromorphic random walk algorithms implement a random walk process by configuring the random behavior of neurons to reflect the desired distribution of transitions between states [13].

3. Theoretical foundations

Pain: Pain is an important physiological phenomenon that exists from birth to the last stages of life, and it is one of the factors for patients to visit clinics and treatment centers.Pain is a complex phenomenon and is still not fully understood.

A very common definition states that pain is an unpleasant sensory and emotional phenomenon that is associated with real or possible tissue damage or describes such damage.However, basic research is still seeking a more advanced understanding of pain, and updating the definition of pain is constantly discussed in the scientific community.From another point of view, pain is a personal experience and has a mental part. The meaning of this word is expressed by each person early in life through his experiences regarding the injuries he has seen [14].

3.1 Concept Neuromorphic:

Recent research in neuroscience and computing has shown that learning and development is a key aspect for neuroscience and real-world applications of cognitive computing. Neuromorphic engineering or abbreviated neuromorphic, which is also called neural computing, is a concept developed in the late 1980s by Carver Mead and means the use of large-scale integrated systems containing electronic analog circuits to mimic neural architecture. And it is biological in the nervous system[15].Neuromorphic computing implements aspects of biological neural networks as analog or digital copies on electronic circuits.The goal of this approach is twofold: to provide neuroscience with a tool to understand the dynamic processes of learning and development in the brain, and to use inspiration from the brain for general cognitive computing. The key advantages of neuromorphic computing compared to traditional approaches are energy efficiency, execution speed, robustness against local failures, and learning ability [16].

In the long term, there is the prospect of using neuromorphic technology to integrate intelligent, energy-efficient cognitive functions into a wide range of consumer and commercial products, from driverless cars to home robots.While strong human-level artificial intelligence remains a mystery, And indeed it may depend on the emergence of an understanding of information processing in the biological brain (through initiatives such as the Human Brain Project) before it becomes a practical reality, there are many cases. Useful applications that can benefit from average cognitive capabilities [17].The neuromorphic computing platform targets researchers in various fields including computational neuroscience and machine learning.Platform users can study network implementations of their choice, including simplified versions of brain models developed on the Brain Simulation Platform or general circuit models based on theoretical work.This platform also offers industry researchers and technology developers the ability to test and test applications based on advanced neuromorphic devices and systems [18].

3.2 FPGA

The array of FPGAs is known as Field Programmable Gate Array. As the name suggests, programmable gates are a platform for implementing ALU logical hardware circuits, the CPU unit.

In common processors such as personal computers, which have based on a set of operational instructions, they are carried out sequentially and sequentially, and if it is necessary to use other operational units, the sequential operation must be stopped and different dimensions of the FPGA To carry out the operation of the unit, to resume the execution of the instructions, but the nature of the desired hardware is completely FPGA, one of these programmable hardware.

It is designed and placed on it.

4. background research

4.1 internal background

Nima Seliminejad, Mahmoud Amiri (2018) In a research inspired by the biology of human tactile perception, a hardware neuromorphic approach is proposed for the mechanical receptor spiking model to encode the input force.Thus, a digital circuit for mechanical type I (SA-I) and fast adaptive type I (FA-I) receivers is designed to be implemented on a low-cost digital hardware, such as a field-programmable gate array. (FPGA) This system computationally replicates the neural firing responses of both afferents. Then, comparative simulations are shown. The spiking models of mechanoreceptors are first simulated in MATLAB and then the digital neuromorphic circuits simulated in VIVADO are also compared to show that the obtained results are in good agreement both quantitatively and qualitatively.Finally, we test the performance of the proposed digital mechanical receivers in hardware using a ready-made test set. Hardware synthesis and physical realization on FPGA show that digital mechanoreceptors are able to reproduce the basic features of different firing patterns including the bursting and spiking responses of SA-I and FA-I mechanoreceptors. In addition to parallel computing, the main advantage of this method is that the digital circuits of the mechanical receiver can be implemented in real time through low-power neuromorphic hardware.This new engineering framework is generally suitable for use in robotic and hand prosthetic applications, thus advancing the state of the art for tactile sensing.

In a research, **Shirmaleki and his colleagues** (1400) did a comprehensive review on the use of neuromorphic in neural processing architecture. Tasks such as object recognition through parallel pattern matching are considered a difficult task for von Neumann computers, but brain-inspired chips can handle these tasks. Unlike von Neumann computers, brain-inspired architectures perform computational tasks through communication pulses between large networks of neurons. Neurons are connected to each other through synapses between each neuron and local storage memory. To activate this chip, neuromorphic architecture in combination with pulsed neurons and stable synapses on a nano scale were presented under the name of memristor or memory resistor. In these systems, neurons generate specific pulse impulses, excite and excite them in a stable synaptic network, and implement instant learning with the rules of biological probability learning [7].

In a research, Shiasi and his colleagues (1400) investigated the types of pain, its control methods and the effect of electrical nerve stimulation on pain. A non-invasive method to diagnose and relieve pain is electrical stimulation of pain inhibitory nerves through the skin. During the use of electrical stimulation of the nerves, pulsed electrical currents are distributed on the surface of the healthy skin to create a strong and painless sensation or soften muscle tension in the pain area. The therapeutic method of electrical nerve stimulation prevents the transmission of information related to pain up in the central nervous system and seems to be useful for acute and chronic pain. In the present study, the effect of using electrical nerve stimulation on all types of pain has been investigated. The findings of this research show that the use of this method has improved the diagnosis and relief of various types of pain in different patients[19].

4.2 Foreign background

Hans P, Anisha K, Lydia E, Alison I. and Suleiman J. (2017) In a research, the understanding of fine textures relies on very precise and repeatable spike patterns that are evoked in tactile afferents. These patterns depend on the microstructure and surface materials, but also on the speed of its movement on the skin surface. Interestingly, texture perception is independent of scan speed, implying the presence of downstream neural mechanisms that correct for scan speed in the interpretation of texture signals from the periphery. What force is applied during texture exploration also has small effects on how the surface is perceived, but the consequences of changing contact force on neural responses to the texture have not been elucidated. In the present study, we measure signals evoked in macaque tactile afferents to a set of tissues scanned across the skin at two different contact forces and find that the responses are largely independent of contact force in the range tested. We conclude that force invariance in tissue perception reflects the independence of tissue representation force in the nerve [20].

Jahyun Kima, Hiso Kima, Subin Hoha, Jin Ho Lieb, Kyung Choya (2018) Spiking neural networks are considered as one of the promising alternatives in research. Techniques to overcome the high energy costs of artificial neural networks It is supported by many researches that a deep convolutional neural network. The network can be transformed into a spiking neural network with accu close to zero. In neural spiking energy consumption due to the use of Poisson, the networks have the cost of long classification delay. In this page, we propose to use weighted spikes, which can greatly reduce the delay. Depending on the time phase that a spike belongs to, it signs a different weight. Experimental results on MNIST, SVHN, CIFAR-10 and CIFAR-100 show that the proposed neural networks with weighted spikes achieve significant results. [4].

Wang and his colleagues (2020) investigated neuromorphic engineering and its challenges in a research. Neuromorphic-based synapses and artificial neurons are the building blocks for forming neural networks to compute acceleration. Furthermore, it enables the implementation of integrated bionic perception and movement systems to mimic the human peripheral nervous system for information sensing and processing. Here, the biological basis is first described, and memory synapses and circuit-simulating neurons used for neuromorphic engineering are discussed and evaluated. And also the mechanisms and computational acceleration and motion integration of bionic perception of neuromorphic systems are discussed. Finally, the challenges and opportunities of neuromorphic engineering to accelerate computations and enrich biomimetic motion perception functions are anticipated [5].

Deng and his colleagues (2021) investigated the simulation of pain receptors based on neuromorphic calculations in a research.Alternative approaches to developing highly stable synapses for neuromorphic systems can be developed with electrical control. The short-term and long-term plasticity of the synapse is realized by the accumulation of volatile electrostatic carriers and proton modulation, respectively.By achieving synaptic functions, an important sensory neuron, the nociceptor, is well simulated in synaptic transistors with all key threshold properties.More importantly, this synaptic transistor exhibits high tolerance to bending deformation.The findings of this research show that the proposed method can simulate the pain receptor well and has high accuracy.[21]

Adeline Bataille, Christelle Le Gall, Laurent Misery, Mathieu Tallagas(2022) Merkel cells (MCs) are rare multimodal epidermal sensory cells. Because of their interaction with low-threshold Aβ mechanoreceptor Aβ1(SA1) afferent neurons (Aβ-LTMRs) to form Merkel complexes, they are considered part of the main tactile end-organ involved in light sensation. This function has been explored over time by ex vivo, in vivo, in vitro and in silico approaches. Exvivostudios has made it possible to determine the topography, morphology and cellular environment of these cells. The interactions of MCs with the surrounding cells are still determined by ex vivo methods, however It is also studied in vitro. Indeed, in vitro models have improved the understanding of the relationship of MCs with other cells in the skin at the cellular and molecular levels. Regarding in vivo methods, the sensory role of MC complexes can be demonstrated by observing physiological or pathological behavior after genetic modification in mouse models. Insilico models are emerging and aim to elucidate the sensory encoding mechanisms of these complexes. The different methods for studying MC complexes presented in this review may allow investigating their involvement in other physiological and pathophysiological mechanisms, despite the difficulties in exploring these cells, especially due to their rarity[22].

5. Research process

In this study, we propose a digital neuromorphic circuit for SA-I receptors (Merkel receptors), and FA-I receptors (Meissner bodies), which are also important cells for surface roughness perception. First, to achieve an efficient real-time hardware implementation in FPGA, the nonlinear differential equations of the mechanical spiking model are simulated in MATLAB. Using several simulations under different conditions, it is shown that the digital circuit mimics the dynamic behavior of the mechanical spiking model simulated in MATLAB, and the results are in good agreement both quantitatively and qualitatively. Finally, we present a test suite to investigate the performance of synthetic SA-I and FA-I receptors in hardware. We provide a quantitative justification of the computational accuracy and also show physical implementation results. The rest of the paper is organized as follows: In the Materials and Methods section, biological concepts and mathematical models of receptor cells are described. The proposed digital circuit is also explained in this section. In the software and hardware simulation results section, the simulation results are discussed. Then, the hardware implementation section describes a test suite to evaluate the real-time performance of the digital receiver in a physical hardware implementation. Finally, the conclusion section concludes the research.

5.1 Methods

methods In this section, we first describe the receivers' spiking models and then present the digital circuit for hardware implementation.

5.1.1 Specking model of electronic receiver

The sense of touch is essential for the survival and growth of multicellular organisms. Forces that affect the skin are encoded by special sensory cells. These tactile receptors in our fingertips, which are selective, sensitive and fast, allow us to touch and manipulate objects well. Depending on this skill, we are able to perform many tasks from the mundane (typing an email) to the superior (playing a Mozart concerto). Slow adapting receptors (SA-I) and (SA-II) are photoreceptors that respond to static pressures and thus fire across stable stimuli. Fast adapting receptors (FA-I) and (FA-II) are other tactile receptors that respond at the onset and initiation of the response. Their actuators respond to vibrations and forces (derivative of force with respect to time). SA-I receptors are located near the surface of the skin and respond to its indentations with high sensitivity. SA-II receptors are located deeper in the skin and are mainly responsible for measuring skin elasticity. Therefore, they are important for proprioception. Both SA-I and FA-I fibers have small receptive fields, while SA-II and FA-II fibers respond to stimulation of large areas of skin.Figure (4) shows a section of glabrous skin.

Primary signals are controlled by neurons in the brainstem nucleus (CN), the brain's first level of tactile processing, which organizes important synaptic relay along the somatosensory pathway from the fingertip to the CNS. The functional link between first- and second-order neurons (mechanoreceptors and spike cells, respectively) has not been fully explored, and computational and experimental findings on how information is processed along this pathway are still needed.

Various models have been proposed to mimic this biological representation. The receptor model has been shown to accurately reproduce the spike trains of type FA-I and SA-I cells over a variety of stimuli. Considering this model and other related models, we consider the sensor output f(t) and it. derivative of f(t), and separate each of them into positive and negative rectified parts that produce four signals. The rectified signals are weighted and summed to convert the current [I(t)] into an Izhikevich neuron model. In this way, the force detected by the sensor, f(t), and the change in the detected force, f(t), in N/ms, are linearly converted to current, I(t), in mA. It should be noted that we used the previously published Izhikevich model, which was shown to be able to reproduce both general receptor types considered, although some papers use the LIF model, which is simpler than the Izhikevich model, with this Currently, LIF models are unable to accurately reproduce the diverse receptor responses obtained in experimental observations. In this design, the Izhikevich neuron model is used because of its ability to demonstrate adaptation, which is a key feature of receptors, and also to reproduce the characteristics of burst and burst responses. The dynamics of the membrane potential, v, of SA-I receptors is as follows:

$$\frac{dv(t)}{dt} = 0.04v(t)^2 + 5v(t) + 140 - u(t) + \frac{K1}{C_m} I(t) \tag{1}$$

$$\frac{dv(t)}{dt} = a\big(bv(t) - u(t)\big) \tag{2}$$

And we have the auxiliary equation as follows:

$$If\ v \geq 30mv \begin{cases} v \leftarrow c \\ u \leftarrow u + d \end{cases} \tag{3}$$

where a, b, c, d are neuron parameters and their values are listed.

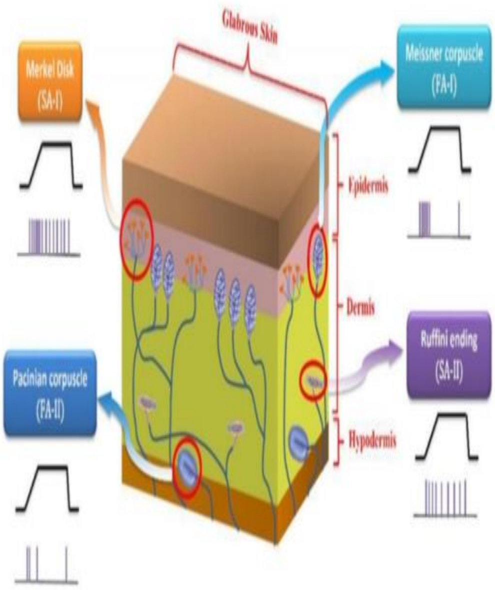

Figure 4: A section of glabrous skin showing a specific type of receptor. Spike trains obtained in response to a specific stimulus are also shown.

Table 1: parameter values of SA-I and FA-I receptor spiking model used in simulations.

Parameter	Spiking	Bursting
a	0.02	0.02
b	0.2	0.2
c	−65	−50
d	6	1.5
V_{th}	30 mV	30 mV
C_m	1	1

Table 1 : u is the membrane recovery variable and I is the input current. The values of parameters a and b can be changed to reproduce different types of compatibility: a specifies the characteristic time of the recovery variable, b determines the sensitivity of the recovery variable. If the membrane potential reaches the threshold value (Vth=30mV), a spike is generated and the membrane voltage and the recovery variable are reset according to (4). The c and d parameters also help to define the adaptation properties of the neuron. The values of parameters a, b, c, and d are chosen to obtain regular and bursty dynamics, which is the case of human finger receptors. Calculations are performed in MATLAB with a time step dt = 0.01ms. Similarly, the following model fits the spiking activity of FA-I receptor cells.

$$\frac{dv(t)}{dt} = 0.04v(t)^2 + 5v(t) + 140 - u(t) + \frac{K2}{C_m}\frac{dI(t)}{dt} \tag{4}$$

$$\frac{du(t)}{dt} = a(bv(t) - u(t) \tag{5}$$

$$If \ \geq 30mv \begin{cases} v \ \leftarrow \ c \\ u \ \leftarrow u + d \end{cases} \tag{6}$$

Indeed, these receptor cell spiking models show promise as efficient computational models for reproducing a wide range of neural responses to stimuli.Two types of receivers, SA-I and FA-I models, described by equations (1)-(6), are used to encode the input force.

5.1.2 Digital neuromorphic mechanoreceptor

In this section, we present a digital receiver mechanical circuit with a new architecture based on the receiver's spiking model. This digital framework may be implemented on low-cost and common hardware platforms such as FPGA. The computational methods used in Von Neumann PCs or SIMD processing units such as GPUs or DSPs are significantly different from the classical methods used for FPGAs. FPGA not only implements a real-time platform with the flexibility of programmable logic, but its ability in parallel and high-speed computing makes it a good choice for designing neuromorphic systems. In fact, FPGAs can significantly improve signal processing speed compared to software-based methods. In recent years, the implementation of digital neural networks on FPGA has attracted considerable attention. And several successful cases have been reported in the literature. The digital circuit for the Merkel mechanical receiver model (SA-I) is first obtained by discretizing its sprinkling model, that is, equations (1) - (3) using Euler's method.

The discrete equations with h = 0.01 ms are as follows:

$$v[n+1] = v\,[n] + h * (0.04 * v[n] * v[n] + 5 * v[n] + 140 - u[n] + \frac{K1}{C_m}\, I[n] \tag{7}$$

$$v[n+1] = h * \big(0.02 * (0.2 * v[n] - u[n])\big) + u[n] \tag{8}$$

Similarly, Discretization of Meissner's receptor-spiking model (FA-I) gives:

$$v[n+1] = v[n] + h * (0.04 * v[n] * v[n] + 5 * v[n] + 140 - u[n]) + \frac{K_2}{C_m}\, (I[n+1] - I[n]) \tag{9}$$

$$u[n+1] = h * \big(0.02 * (0.2 * v[n] - u[n])\big) + u[n] \tag{10}$$

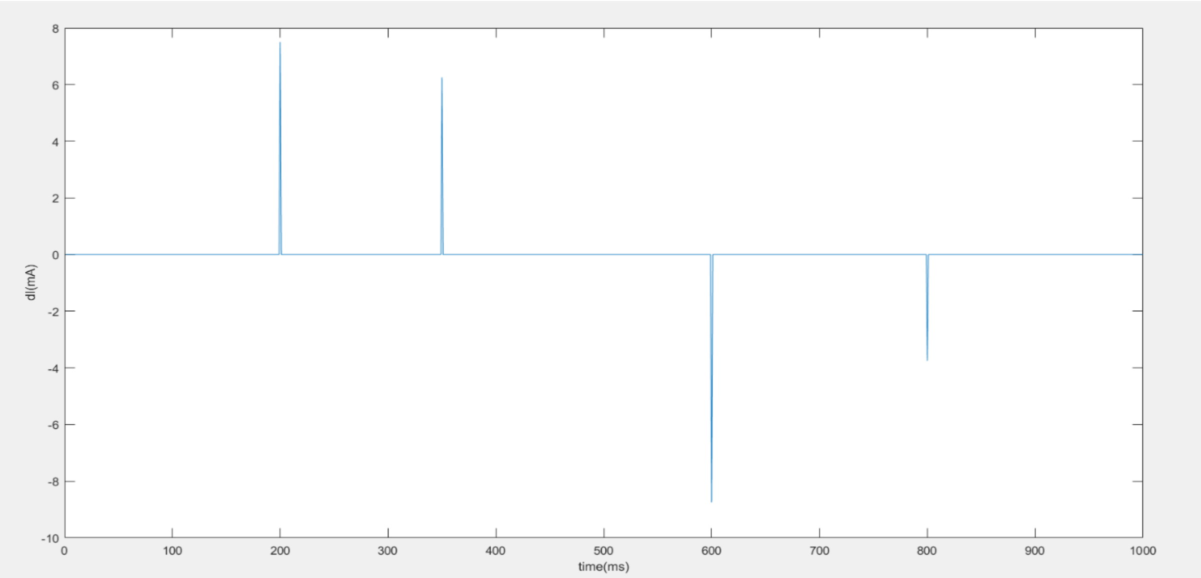

Figure 5: Merkel cell (SA-I) and Meissner receptor (FA-I) model. The FA-I receptor responds with action potentials during stimulus onset and offset. The SA-I receptor is active during the period of contact with the stimulus. Izhikevich model was used to generate spiking/bursting responses.

Considering the equations (7)-(10), it describes the steps necessary to generate the membrane potential (v) and the recovery variable (u) of the receptor model in one iteration. This process is done to generate a single output sample using the latest samples. In each block, a memory register is used to store the outputs, which are used in the next steps of calculations. Each state variable is resolved into N-bit registers. "N" is the length of the register and is determined by the precision required for execution. This directly affects the computational time and cost. In this research, we set N = 32 to obtain a circuit with low error, low cost and high speed. Finally, the desired signals are converted to analog signals using a digital-to-analog converter chip. MAX5216PMB1 module is used in this work. This digital system based on receptor dynamic reproduction proposes a neuromorphic conversion of the input signal (sensor output) into spike/burst patterns that convey tactile information as seen in natural tactile coding. Since there are no costly operations to slow down the critical paths, a reduction in area and an increase in the maximum frequency of operations are anticipated. As a result, less hardware resources are required for the proposed digital receiver. The digital circuit proposed in this study to adapt the features of the spiking model of the receptors can be extended to different types of silicon designs with the same complexity as the spiking neuron

5.1.3 The results of software and hardware simulations

In this section, the results of the software simulation of the receiver spiking model in MATLAB and the proposed digital neuromorphic circuit are described. We show how the digital circuit retains the essential features of its spec counterpart.Both MATLAB simulations were performed using the same dt = 0.01ms.

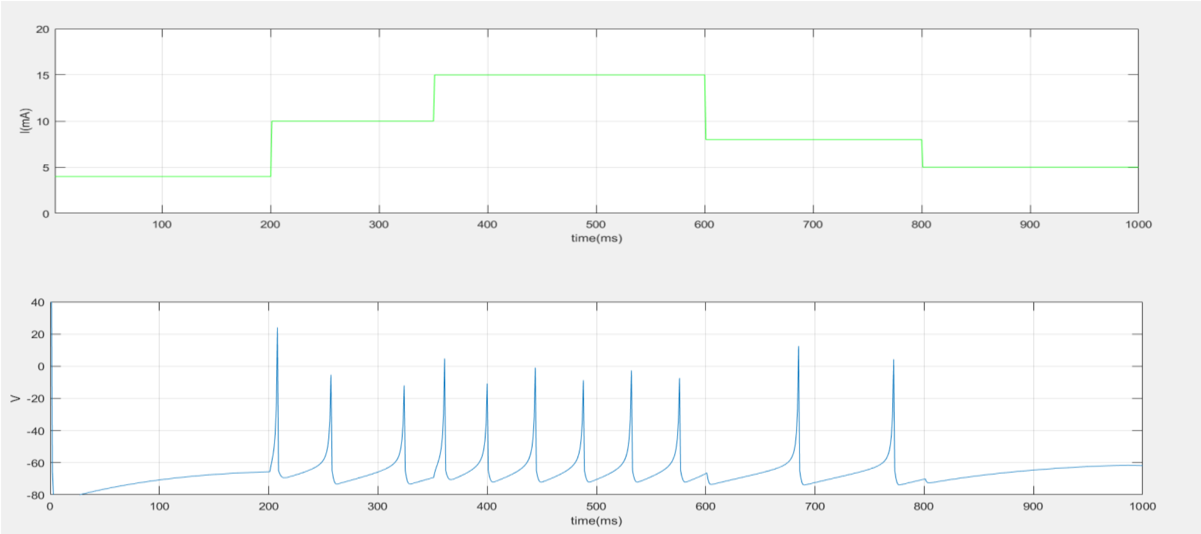

Figure 6: Time response of the Merkel cell receptor (SA-I) In these simulations, the first panels show the input signal, the second panels show the MATLAB simulation of the spiking receptor model.

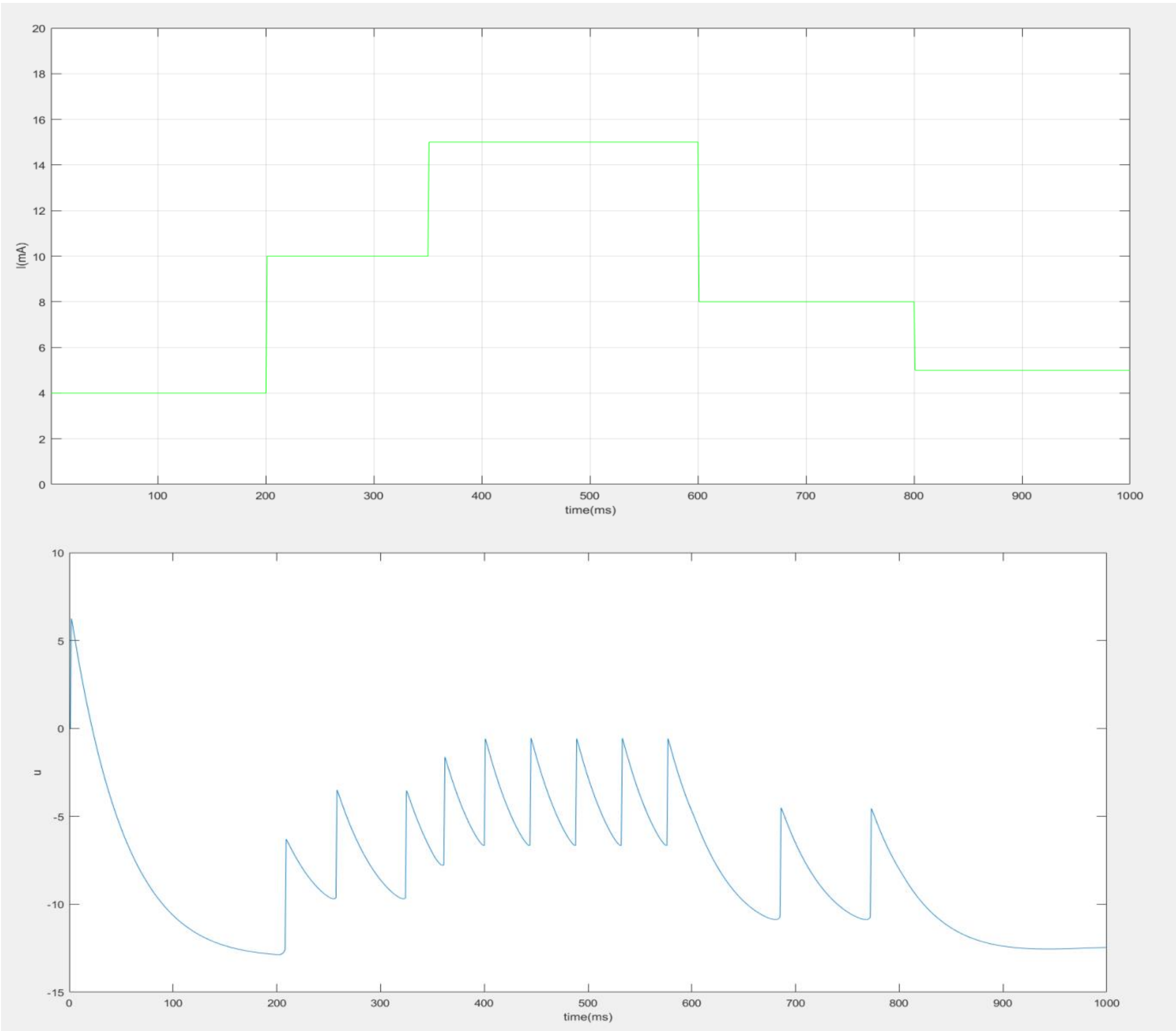

Figure 7: Time response of Meissner receiver (FA-I)

In these simulations, the first panels show the input signal,The second panels show MATLAB simulations of the spiking receptor model.

Table 2:Mean and variance of ISI and IBI values for two types of receivers using MATLAB simulation

		ISI		IBI	
		Average	Variance	Average	Variance
SA-I	MATLAB	37.8550	0.0025	57.8538	0.0025
FA-I	MATLAB	199.7000	1633.5800	197.5667	1620.0156

To demonstrate the flexibility of the designed circuit and to compare its capabilities and behavior with the receiver's spiking model, several simulations have been performed.

Figures 6 and 7 show burst and burst reactions, respectively, for Merkel cells (SA-I) and Meissner's body (FA-I).In these figures, the first panels show the staircase pulse as the input signal.

The second panels show MATLAB simulations of the spiking receptor model.

According to these results, both answers spiking and bursting can be noticed and Hence, the digital circuit can work in both regimes.It should be noted that the model parameters for spiking and bursting patterns are shown in Table 1.

Referring to Figures6 and 7, SA-I receptors fire throughout a sustained stimulus and FA-I receptors respond at the onset and onset of that stimulus.

This result is consistent with the response obtained by the observations reported in Jöntell et al.

In other words, the spiking receptor model, inspired by the biology of human tactile perception, and a proposed digital receptor circuit produce temporal responses that functionally match the spiking activity of receptor cells.

We continue our simulations. For this purpose, we calculate the mean and variance of the inter-spike interval (ISI) and interburst interval (IBI) of the results shown in Figures 6 and 7, which are reported in Table 2.

In fact, the response of each neuron is characterized by the spike time and these incremental responses contain information. Consequently, ISI and IBI are important factors that must be considered and compared to validate the responses obtained by the proposed digital circuit.

Table 2, shows the mean and variance values of ISI and IBI obtained by MATLAB simulation of the proposed digital receiver model.

According to Table 2, we expect that the errors due to the approximation of the discrete equations are small and therefore the spike timing (a fundamental component in the brain's information processing) is consistent.

Finally, the performance of the proposed digital circuit is analyzed from a dynamic point of view.

5.1.4 Hardware implementation

The entire diagram for hardware testing of the proposed digital receiver mechanics is shown in Figure 8. This platform encodes the force recorded from the sensor to the spiking activity of the receiver's digital circuit he does.

In fact, the force detected in the sensor is converted into a current which in turn generates an action potential string. This is analogous to how stress and/or strain applied to a receptor end organ is converted into current across its membrane. To validate the proposed digital design for the receiver model, it has been implemented on the ZedBoard development kit. The platform's extensibility features enable rapid proof-of-concept development and prototyping. The main objective is to investigate the feasibility of FPGA implementation of the circuit, especially to benefit from reconfigurable hardware blocks and parallel processing.

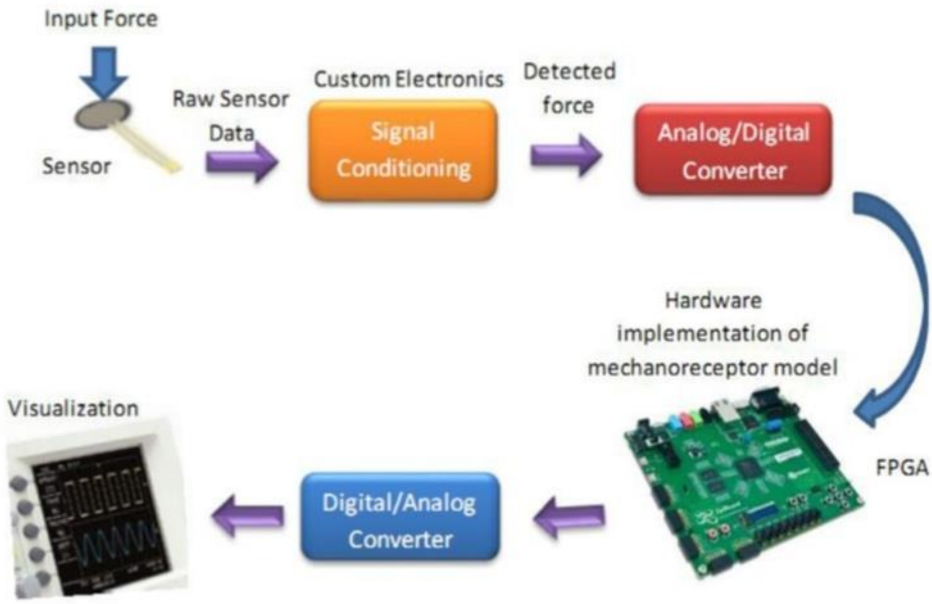

Figure 8: Hardware test diagram of receiver digital circuit. In this case, the digital receiver is implemented on the ZedBoard and the received signals are displayed on the oscilloscope after being converted to analog signals. A 10-bit ADC was used for analog-to-digital conversion. However, a 16-bit DAC was used to convert the ZedBoard's digital outputs to analog signals for display on the oscilloscope.

Table 3: Summary of ZedBoard device usage

	Used in SA-I	Used in FA-I	Available
Slice LUTs	975	1131	53,200
Slice Registers	65	97	1,06,400
Slice	268	309	13,300
LUT Flip Flop Pairs	60	60	53,200
DSP48	16	18	220
Bonded IOB	12	12	200

The first component in Figure 8 is the force sensor. Force-sensitive resistors (FSR) are commercially available and easily integrated with peripheral hardware and software. It is designed to measure the presence and relative amount of local physical pressure. FSR separated by two layers, as the pressure increases, these points come into contact with the active semiconductor elements, so that the resistance decreases. In other words, it can be thought of as a resistor that changes its resistance value with the amount of resistance pressure (in ohms,) that depends on the amount of suppression. The FSR responds to a normal force in the range of 0.2-20N in its thin, circular pressure-sensitive region. The voltage passing through the sensor is first amplified and then filtered to a 10-bit ADC (analog-to-digital converter) that collects data at a sampling rate of 200 kHz.

The current detected at the sensor, f(t), is converted to a current (Figure 5) to be injected into the digital receiver as an input current. Following the method mentioned in, a wide range of values for the increase factors (K1) and (K2) have been tested. Large values induce strong stimulus-independent firing rate increases and lead to a less informative temporal structure of spikes. However, low gain factors lead to low firing rates and thus long latencies in spike responses, after appropriate trade-offs we reached K1 = 0.75 and K2 = 3. Then, the input stream is converted into spike/burst trains using the digital receiver implemented in the ZedBoard.

As the range of detected force increases, the frequency of spike/burst patterns also increases. This approach enables the decoding of stimuli while collecting the tactile data stream. This is indeed consistent with experimental observations where different stimulation patterns evoked the total number of spikes. The results obtained are for the digital realization of the FA-I receiver. The device usage for realizing both SA-I/FA-I digital circuits is summarized in Table 3.

To cover more input signals in addition to the step signal, various inputs such as sinusoidal, triangular, and pulsed are also applied to the FPGA when implementing digital receiver circuits. To provide a quantitative analysis, the physical outputs of digital receivers (ZedBoard) with MATLAB simulation of the continuous speaking models of Equations (1) and (2) solved by the Runge-Kutta method, (RK4) and discrete (Equations 7, 8) are compared An input signal with four different amplitudes is used to compare the performance.

Figures 5 and 7 show the responses obtained that are fully matched for a particular input. To compare the firing patterns produced by the digital realization with the computational patterns, ISI values were calculated and reported in Table 3.

The very small relative error (Table 3, last column) between the ISI values obtained by the MATLAB simulation and the digital realization on an FPGA indicates acceptable performance and thus the proposed digital circuit is faithful. Although this analysis does not support the validity of the model from a biological point of view, it shows that the digital circuit implemented on the FPGA correctly follows the spiking model, which is a necessary step for moving forward and further analysis. . The digital circuit produces satisfactory responses according to the main criteria in terms of hardware, such as increasing the scale of the circuit, reducing the cost of digital realization and achieving results similar to the receiver's computational model. Finally, this neuromorphic approach can offer the possibility of mimicking the sense of touch with flexible design features to evaluate the related effects. It also supports the design of new architectures for artificial tactile sensory systems for rehabilitation applications.

6. Conclusion

Given performance, power, and time constraints, recent advances in FPGA technology support the flexibility needed for algorithmic exploration. By discovering the fundamental mechanisms in neuroscience and translating them into hardware realizations, current technologies can be advanced. These new neuron-inspired technologies have several real-world applications, including adding sensory capabilities to provide information about body position (proprioception) and grip forces.

Table 4: The ISI values (in milliseconds) for the spiking responses calculated using the MATLAB simulations and the FPGA implementation correspond to the different sections of Figure 8

ISI / Figure 14	MATLAB		Physical implementation on the ZedBoard	Relative Error
	Continuous Diff. Equations (1) and (2) solved by RK4	Discrete Diff. Equations (7) and (8)		
A	48.6	48.6	48.5	0.002
B	44.5	44.7	45	0.011
C	41.2	41.3	41.5	0.007
D	38.5	38.4	39	0.012

The present research opens a new window for the analysis of mechanical receptors in hardware. To overcome the problems of analog fabrication, digital implementation was used in this research. We proposed a digital neuromorphic circuit in both software simulation and hardware realization . The system was shown to reproduce spike/burst patterns and is mainly designed for applications that require efficient and low-power hardware systems.In this way, the proposed circuit enables us to design a hardware architecture to run on an FPGA The segmented digital circuit structure and the ability to control the mechanical receiver parameters make it easy to add additional mechanisms without extensive circuit redesign.

This helped to easily scale the model to include a larger number of receivers in a single FPGA. This engineering approach is a novel way to construct sensory systems that artificially replicate SA-I and FAI firing activities. It should be noted that the proposed digital receiver has the minimum level of biological acceptability, in the sense that for the Merkel digital receiver, the firing rate increases with higher forces, and for the Meissner digital receiver, the firing rate changes based on the force change rate. However, in this digital realization, the structure of the mechanical receptors was neglected and the input/output characteristics were considered.

7. Future work

In this research, a hardware neuromorphic approach is proposed for the spiking model of receptors to encode the input force. Parameter sensitivity analysis and comparison of digital realization results with biological data should be explored in the future development of this approach. Future work will be done to include other receiver models. Additionally, by implementing a large population of digital receptors, the development of a new generation of prosthetics also provides sensory feedback for people with skin damage or amputations. Spike/burst trains obtained from digital receptors may be passed to a brainstem spiking model (which can also be implemented in hardware) for further processing. It creates a neuromorphic sensory system that is used on a mobile robot to perform various real-world tasks such as texture recognition and object recognition.

8. Refrence:

[1] Ronchini M, Rezaeiyan Y, Zamani M, Panuccio G, Moradi F. NET-TEN: a silicon neuromorphic network for low-latency detection of seizures in local field potentials. Journal of Neural Engineering. 2023 May 5;20(3):036002.

[2] Park B, Neuberger T, Webb AG, Bigler DC, Collins CM. Faraday shields within a solenoidal coil to reduce sample heating: Numerical comparison of designs and experimental verification. Journal of Magnetic Resonance. 2010 Jan 1;202(1):72-7.

[3] Fares H, Ronchini M, Zamani M, Farkhani H, Moradi F. In the realm of hybrid Brain: Human Brain and AI. arXiv preprint arXiv:2210.01461. 2022 Oct 4.

[4] Rathi N, Chakraborty I, Kosta A, Sengupta A, Ankit A, Panda P, Roy K. Exploring neuromorphic computing based on spiking neural networks: Algorithms to hardware. ACM Computing Surveys. 2023 Mar 2;55(12):1-49.

[5] Wang S, Chen X, Huang X, Wei Zhang D, Zhou P. Neuromorphic engineering for hardware computational acceleration and biomimetic perception motion integration. Advanced Intelligent Systems. 2020 Nov;2(11):2000124.

[6] Milo V, Malavena G, Monzio Compagnoni C, Ielmini D. Memristive/CMOS Devices for Neuromorphic Applications. Springer Handbook of Semiconductor Devices. 2022 Nov 11:1167-99.

[7] Shirmaleki S, Azmi R, Layeghi K. A comprehensive review of neuromorphic application in neural processing architecture. 2021; 3(5).

[8] Vickers NJ. Animal communication: when i'm calling you, will you answer too?. Current biology. 2017 Jul 24;27(14):R713-5.

[9] Stewart TC, Eliasmith C. Large-scale synthesis of functional spiking neural circuits. Proceedings of the IEEE. 2014 Mar 27;102(5):881-98.

[10] Yang W, Jin Z, Thiem C, Wysocki B, Shen D, Chen G. Autonomous target tracking of UAVs based on low-power neural network hardware. InMachine Intelligence and Bio-inspired Computation: Theory and Applications VIII 2014 May 22 (Vol. 9119, pp. 192-200). SPIE.

[11] Aimone JB, Date P, Fonseca-Guerra GA, Hamilton KE, Henke K, Kay B, Kenyon GT, Kulkarni SR, Mniszewski SM, Parsa M, Risbud SR. A review of non-cognitive applications for neuromorphic computing. Neuromorphic Computing and Engineering. 2022 Sep 2;2(3):032003.

[12] Smith JD, Hill AJ, Reeder LE, Franke BC, Lehoucq RB, Parekh O, Severa W, Aimone JB. Neuromorphic scaling advantages for energy-efficient random walk computations. Nature Electronics. 2022 Feb;5(2):102-12.

[13] Aimone JB, Lehoucq R, Severa W, Smith JD. Assessing a neuromorphic platform for use in scientific stochastic sampling. In2021 International Conference on Rebooting Computing (ICRC) 2021 Nov 30 (pp. 64-73). IEEE.

[14] Murbach M, Neufeld E, Kainz W, Pruessmann KP, Kuster N. Whole-body and local RF absorption in human models as a function of anatomy and position within 1.5 T MR body coil. Magnetic resonance in medicine. 2014 Feb;71(2):839-45.

[15] Aimone JB, Hill AJ, Severa WM, Vineyard CM. Spiking neural streaming binary arithmetic. In2021 International Conference on Rebooting Computing (ICRC) 2021 Nov 30 (pp. 79-83). IEEE.

[16] Fischl KD, Andreou AG, Stewart TC, Fair K. Implementation of the neural engineering framework on the TrueNorth neurosynaptic system. In2018 IEEE Biomedical Circuits and Systems Conference (BioCAS) 2018 Oct 17 (pp. 1-4). IEEE.

[17] Ielmini D, Ambrogio S. Emerging neuromorphic devices. Nanotechnology. 2019 Dec 9;31(9):092001.

[18] Najmaei S, Glasmann AL, Schroeder MA, Sarney WL, Chin ML, Potrepka DM. Advancements in materials, devices, and integration schemes for a new generation of neuromorphic computers. Materials Today. 2022 Oct 1;59:80-106.

[19] Shiasi F, Yousefi MR. The study of pain types, its inhibitory methods and tens effect on pain. Journal of Intelligent Procedures in Electrical Technology. 2021 May 22;12(45):17-33.

[20] Habibi Aghdam H, Jahani Heravi E, Habibi Aghdam H, Jahani Heravi E. Convolutional neural networks.

[21] Deng X, Wang SQ, Liu YX, Zhong N, He YH, Peng H, Xiang PH, Duan CG. A flexible mott synaptic transistor for nociceptor simulation and neuromorphic computing. Advanced Functional Materials. 2021 Jun;31(23):2101099.

[22] Shahraki, M, Mesgar, M, comparison of data-mining algorithms for diagnosis of liver diseases. 2018; 13(1).

[23] Melzack R. Pain and the neuromatrix in the brain. Journal of dental education. 2001 Dec;65(12):1378-82.

[24] Cho SW, Jo C, Kim YH, Park SK. Progress of materials and devices for neuromorphic vision sensors. Nano-Micro Letters. 2022 Dec;14(1):203.

[25] Frueh FW, Amur S, Mummaneni P, Epstein RS, Aubert RE, DeLuca TM, Verbrugge RR, Burckart GJ, Lesko LJ. Pharmacogenomic biomarker information in drug labels approved by the United States food and drug administration: prevalence of related drug use. Pharmacotherapy: The Journal of Human Pharmacology and Drug Therapy. 2008 Aug;28(8):992-8.

[26] Nava MB, Bertoldi S, Forti M, Catanuto G, Vergnaghi D, Altomare L, Tanzi MC, Farè S. Effects of the magnetic resonance field on breast tissue expanders. Aesthetic plastic surgery. 2012 Aug;36:901-7.

[27] Park BS, Razjouyan A, Angelone LM, McCright B, Rajan SS. RF Safety evaluation of a breast tissue expander device for MRI: numerical simulation and experiment. IEEE transactions on electromagnetic compatibility. 2017 Mar 29;59(5):1390-9.

[28] Park B, Webb AG, Collins CM. A method to separate conservative and magnetically-induced electric fields in calculations for MRI and MRS in electrically-small samples. Journal of Magnetic Resonance. 2009 Aug 1;199(2):233-7.

[29] Tuchman Y, Mangoma TN, Gkoupidenis P, Van De Burgt Y, John RA, Mathews N, Shaheen SE, Daly R, Malliaras GG, Salleo A. Organic neuromorphic devices: Past, present, and future challenges. MRS Bulletin. 2020 Aug;45(8):619-30.

[30] Yu J, Wang Y, Qin S, Gao G, Xu C, Wang ZL, Sun Q. Bioinspired interactive neuromorphic devices. Materials Today. 2022 Nov 1;60:158-82.

[31] Sanei S, Chambers JA. EEG signal processing. John Wiley & Sons; 2013 May 28.

[32] Subha DP, Joseph PK, Acharya U R, Lim CM. EEG signal analysis: a survey. Journal of medical systems. 2010 Apr;34:195-212.

[33] Lakshmi MR, Prasad TV, Prakash DV. Survey on EEG signal processing methods. International journal of advanced research in computer science and software engineering. 2014 Jan;4(1).

[34] Siuly S, Li Y, Zhang Y. EEG signal analysis and classification. IEEE Trans Neural Syst Rehabilit Eng. 2016;11:141-4.

[35] Hazarika N, Chen JZ, Tsoi AC, Sergejew A. Classification of EEG signals using the wavelet transform. Signal processing. 1997 May 1;59(1):61-72.

[36] Ajwani RD, Lalan A, Bhattacharya BS, Bose J. Sparse distributed memory using spiking neural networks on Nengo. arXiv preprint arXiv:2109.03111. 2021 Sep 7.

[37] Azad F, Zare M, Amiri M, Keliris GA. Analysis of the spike responses in the neuromorphic implementation of the two-compartmental model of hippocampal pyramidal neuron. Journal of Computational Science. 2023 Jan 1;66:101909.

[38] Elnagar S, Thomas MA, Osei-Bryson KM. What is Cognitive Computing? An Architecture and State of The Art. arXiv preprint arXiv:2301.00882. 2023 Jan 2.

[39] Tahitran, A, Bakshaish I, Hosseininejad, M., Azari, P., Kazemnejad, E. Investigation of pain syndromes after stroke and their risk factors, 2021 Dec; 21(82).

[40] Thevenot J, López MB, Hadid A. A survey on computer vision for assistive medical diagnosis from faces. IEEE journal of biomedical and health informatics. 2015 Oct 5;22(5):1497-511.

[41] Lu W, Rajapakse J. Constrained independent component analysis. Advances in neural information processing systems. 2000;13.

[42] Ma Y, Guo G, editors. Support vector machines applications. New York: Springer; 2014 Mar 3.