Resonate-and-Fire Neurons for Radar Interference Detection

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ABSTRACT

Radar devices sense the environment and detect range, velocity, and angel of arrival by applying multiple Fourier transformations. However, these calculations are expensive and assume that the data are in memory. Frequency-Modulated-Continuous-Wave sensors are primarily used in the automotive industry but are affected by signal superposition with other sensors. It can introduce ghost targets or increase the noise such that low reflective targets are lost. Inspired by the energy efficiency of Spiking Neural Networks, we show that Resonate-and-Fire neurons are able to encode the temporal radar signal into spikes and use a population of Leaky Integrate-and-Fire neurons to distinguish between the normality and patterns such as interference or saturation. We use simulations to prove the concept and achieve in this preliminary study an average accuracy of 85% by utilizing Back-Propagation Through Time with surrogate gradient learning.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; • **Computer systems organization** → *Embedded systems.*

KEYWORDS

Resonate-and-Fire, Spiking Neural Network, FMCW, RADAR, Interference

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1 INTRODUCTION

The increasing level of autonomy in automobiles and the growing number of vehicles with advanced driver assistance systems drive the necessity of a precise and reliable environment perception. One key element of these perception systems is the Radio Detection and Ranging (RADAR) sensor, which transmits electromagnetic signals at carrier frequencies around 77 GHz [13] and perceives its environment based on the received reflections. Unlike cameras, the radar sensor works in various conditions, such as low light and bad weather.

In the automotive industry, the Frequency-Modulated-Continuous-Wave (FMCW) modulation scheme is commonly used in which the carrier frequency is linearly modulated over time. During short measurement intervals, the emitted signal frequency continuously increases. The temporal delay introduced by the round trip time of the reflected signal expresses itself in a frequency difference between the received signal and the currently emitted waveform. Thus, this frequency difference is proportional to the distance between emitter and target.

Every radar emitter can modulate the transmit signal freely as long as it adheres to the official regulations. The modulation scheme can differ, for example, in the measurement intervals' length, the frequency modulation's slope, and the length and order of active and inactive periods. In a limited frequency band with multiple RADAR sensors operating simultaneously, the likelihood of signal superposition increases. This superposition is interference and can either introduce ghost targets or increase the noise level. Targets with a low reflective power could be lost in the noise level of non-coherent interference [6]. Thus, it is crucial to detect interference to ensure the assistance systems' reliability and prevent accidents. The system has to inform the user or mitigate the effect of interference. [2, 17] analytically investigate radar interference.

Current approaches to detect the interfered signal sections comprise streaming evaluations like the detection of sudden increases of the signal amplitude or the machine learning-based analyses of complete measurements in the time domain [8] or the frequency domain [15]. The limitations of these approaches are either the limited ability to detect interference scenarios or the restricted compute performance and power budget in this embedded application.

In this work, we explore the use of Spiking Neural Networks (SNNs) in this application. Their energy-efficient event-based computation scheme renders them an interesting opportunity for detecting complex patterns in restricted environments [3]. SNNs process information by exchanging all-or-nothing pulses – spikes – between neurons. In contrast to common artificial neural networks, this enables an energy-efficient time-based computation scheme,

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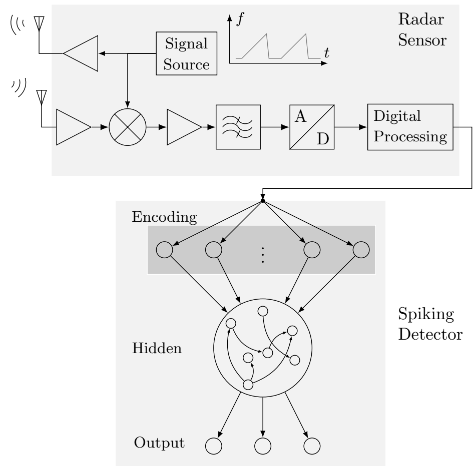

Figure 1: Block-diagram of the Radar sensor and the connection of the proposed pattern detector for interference detection. The spiking network architecture with ResFire input stream encoding and the hidden population of LIF neurons. The output is the membrane potential of the output neurons without leak and spike mechanism.

in which only those parts of the network are updated where spikes are emitted [4].

We use Resonate-and-Fire (ResFire) neurons to convert the continuous signal into a frequency-dependent spike representation. Therefore, the ResFire oscillates with the resonate frequency, and the threshold suppresses the noise component. These spikes are forwarded into a hidden population of Leaky Integrate-and-Fire (LIF) neurons, and the output uses Leaky Integrator (LI) with an insignificant leak.

In the first step, we apply the approach in discrete time steps on the discretized and quantized signal. However, the approach is not limited to a purely digital implementation. With analog implementations of the ResFire and LIF neurons, as shown by [10, 11], the entire interference detection can be realized before the analog-to-digital conversion.

2 NEURON MODELS

The architecture for the differentiation between normal, interference, and saturation is shown in Figure 1. It consists of an encoding, hidden, and output layer of fully spiking neurons. The data are converted into spikes after the analog-to-digital conversion in the radar sensor. In the following, we will describe the dynamics of the different neurons of the architecture.

2.1 Resonate-and-Fire Neuron

The encoding layer consists of ResFire neurons, which transform the time domain signal into a temporal-spatial representation of the frequency components. Originally, the neuron was found by Izhikevich [9] to simulate an oscillatory membrane potential inspired by biological observation. Afterward, [1] showed that these neurons have similarities to the traditional Fourier transform.

The ResFire neuron represents a damped oscillation of the membrane potential and therefore provides some very interesting properties. Izhikevich has proposed the neuron subthreshold dynamics as the following linear system [9]:

$$\dot{v} = \begin{bmatrix} b & -\omega \\ \omega & b \end{bmatrix} v + \begin{bmatrix} i \\ 0 \end{bmatrix} \tag{1}$$

where the resonant frequency of the neuron is defined by the angular frequency $w = 2\pi f$ and the damping factor b affects the time to reach zero amplitude of the oscillation. We use in all our simulations the damping factor of -1. In our simulations we use the exact solution of the given differential equation by utilizing the exact integration method proposed by [16], hence we can define the discrete representation of the ResFire neurons as

$$\underline{z}[n] = \underbrace{\mathrm{e}^{\Delta t\, b}}_{=\lambda}\ \mathrm{e}^{\mathrm{j}\,\Delta t \omega}\ \underline{z}[n-1] + i[n], \tag{2}$$

where Δt is the simulation step size. With the Euler formula, the equation can be reformulated to cosine and sinus representation, where the damping factor λ and the oscillation kernel $\Delta t\, w$ can be precalculated for every neuron.

The generation of an output action potential is similar to the LIF, which we use as hidden neurons. If the voltage-like variable $Im(\underline{z})$ exceeds a predefined threshold ϑ, the neuron generates a spike $\delta(t)$ and the internal states are reset.

$$\delta[n] = \begin{cases} 1, & \text{if } \mathrm{Im}(\underline{z}[n]) > \vartheta \rightarrow \underline{z}[n] = 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

In [12] they use a different threshold method by forcing to spike only at the peak of the oscillation and not in the rising edge by detecting the zero transition of the current-like variable $Re(\underline{z})$. This additional complexity ensures a constant inter-spike-interval but would increase the requirements for an analog implementation of the neuron. Therefore, we focus on the usage of the simpler threshold method. An exciting side effect of the threshold is the early suppression of noise by focusing on higher amplitude oscillations. After the threshold is exceeded, the neuron states are reset. In the original work, only the real component was reset to zero such that the neuron's damped oscillation could continue, which provides an important feature for spike-based inputs. With continuous input values, such a threshold increases the number of spikes and adds instability to the symmetric frequency detection, which we could observe during our simulations. Thus, we use the approach to reset the complete neuron to zero, and if the frequency still exists in the input, the neuron's oscillation starts to increase again.

2.2 Leaky Integrate-and-Fire

As hidden neuron population, we use the LIF neuron due to its computational performance. The neuron's subthreshold dynamics are

$$\dot{v} = \frac{-v + i}{\tau_{\mathrm{mem}}}, \tag{4}$$

where v represents the membrane potential and i the input current, consisting of the superposition of the alpha-shaped input spikes. The neuron integrates the incoming current of the weighted spikes for the forward and recurrent connection. When $v > \vartheta$, then the neuron has exceeded the threshold and emits an action potential with a membrane potential reset to zero. We refer to [5] for more details about the neuron and the corresponding documentation of the Norse simulator [14].

The readout neuron is a variation of the LIF neuron without the firing and reset mechanism and is, therefore, called LI. In this application, the leak is insignificant, but it provides the capability of forgetting information and of detecting the exact time of interference. Each readout neuron represents the prediction probability of each class.

3 NETWORK TOPOLOGY AND TRAINING

The spiking network is connected with the radar sensor after the digital processing of the Analog-Digital-Converter (ADC) as shown in Figure 1. Furthermore, it indicates the organization of the network, comprising an encoding, hidden, and output layer.

The radar data, consisting of 1024 sample points, are propagated as streams to the encoding layer without using weights. The encoding consists of 100 ResFire neurons, where each neuron has a different resonate frequency. We use a linear scale with the frequency step size of 100 kHz. The encoding layer is fully connected with the hidden population, consisting of 50 LIF neurons with dense recurrent connections. The output or readout layer consists of three leaky integrators representing the integration of the events in the membrane potential. We use three classes to identify the normal, interference, and saturation pattern. Saturation can occur due to the fact that the interfere has a high transmit power and is close to the sensor. For the network simulation, we use the Norse simulator [14] that utilizes the surrogate gradient learning to enable Back-Propagation Through Time (BPTT). We omit the training of the encoding layer because the difference between the threshold and the membrane potential varies due to the oscillating behavior of the neuron. Therefore, we focus the training on the hidden population of recurrent LIF neurons. The negative-log-likelihood loss function minimizes the error between the true and the predicted class by using the logarithmic softmax function of the readout neuron membrane potential at the final time step. During training, we use class weights to overcome the unbalanced occurrence of the classes.

4 EXPERIMENTS AND RESULTS

We use a simulator to generate the radar signal with random targets with various range, angle, and velocity settings. The chirp sequence of the sensor under test, who is the victim, is kept constant because it corresponds to real implementations. The aggressor chirp sequence varies because not every sensor is the same. Therefore, we use the same simulator and limits as described in [8]. The radar time series is separated into consecutive chirps and invalid regions, such as the wait time between chirps is removed. Therefore, we use the same data as typically for the signal processing pipeline. Our victim radar uses 8 chirps where different interference could affect the signal. Hence, the dataset consists of 22781 training and 2531 test chirps with randomly generated targets. The dataset differs to [8] because we use additionally the saturation class, which appears during very strong interference or due to close targets. The train and test set have a similar class distribution; on average 66% are

Table 1: Simulation results of the proposed architecture with an overall accuracy of 85%

class	precision	recall	f1-score
normal	0.83	0.97	0.90
interference	0.83	0.43	0.57
saturation	1.00	1.00	1.00

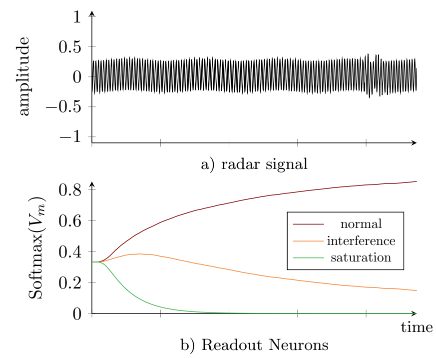

Figure 2: The encoding layer suppresses the low amplitude interference and focuses on specific signal components. a) shows an exemplary radar signal and b) the corresponding readout potential without the detection of interference.

the normal class, 21.5% represent interference, and 12.5% of the samples are saturated.

We utilize standard statistical methods [7], such as precision and recall, to show the efficiency of the interference detection method. Table 1 shows the examples of the best performing architecture, which is shown in Figure 1. The class saturation is detected very well since the signal has a high amplitude, and many spikes are generated during the encoding stage. The missed detections of the interference class come from the low amplitude interference for a short duration, which has a minor effect on the overall signal processing and are very difficult to detect due to the noise suppressing effect of ResFire neurons. The high precision and low recall mean fewer samples are detected as interference, but most detected ones are actual interference. Figure 2 shows the radar signal with interference, where the readout neurons cannot detect it because the ResFire neurons suppress the interference activity due to the low amplitude. The false detected interference samples are also very interesting because some classify the sample very early as interference, and the reason could be that interference not only affects the valid sample points but also the signal outside of the window and can negatively affect the beginning of the series. The accurate labeling of the anomalies is complex in the time-domain signal. The Figure 3 shows an exemplary classification of the interference class. The encoded spike train shows the interference as a V-shaped spike activity. The reason for this activity is that the received signal is mixed with the transmit signal to extract the frequency difference that is proportional to the time of flight between the sensor and targets. A complete crossing of the instantaneous frequency during interference leads from a negative to a positive frequency and is

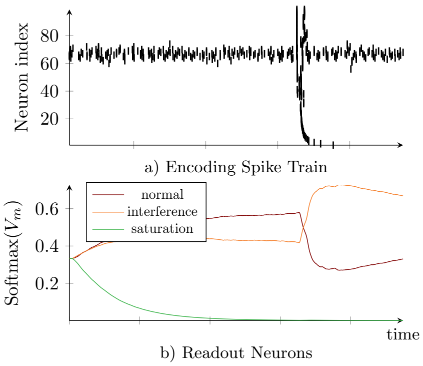

Figure 3: Example of an interfered radar signal. a) is the spike train of the encoding layer with visible interference, and b) shows the softmax function of the membrane potential of the readout neurons with rapid change of the classification due to interference.

in the center zero [17], which is also shown by the spike train in Figure 3. The longer period of lower resonant frequency ResFire neurons (smaller index) explains the temporal spike shift. The readout neuron indicates a rapid change at the time of interference from the normal to the interference class. Afterward, the certainty about the interference class decreases because the signal is again normal. We observed that readout neurons with a smaller membrane time constant are able to indicate faster changes, which we tried to avoid for the classification of a complete ramp. The hard threshold mechanism of the ResFire neurons provides two properties: 1) noise suppresses and 2) low sensitivity to low interference amplitude. The encoding stage already focuses on stronger signal components and removes low amplitude signals such as interference and noise.

5 CONCLUSION AND FUTURE RESEARCH

The detection of failures is essential in various applications, so far there is not a single solution for everything. Therefore, we focus on detecting interference and saturation by only analyzing the radar ramp signal. We show the spike encoding with ResFire neurons and the spike-based processing of a LIF population. However, the performance of the proposed system is reduced due to the fact that ResFire neurons suppress noise and low amplitude signals, which can even be seen as an advantage because the undetected interference patterns do not influence the signal processing and low reflective targets can still be detected.

Furthermore, the used dataset is limited because of a missing definition of the strength of disturbance, which affects the overall performance of the detection. A public dataset with labels and the strength of interference could increase the comparability of approaches. The future research is inspired by the idea to overcome the ADC and to enable event-driven processing in analog hardware to reduce the system's energy consumption by simultaneously removing noise. Therefore, we investigate approaches to continuously detect interference in the radar signal to show that SNNs are potential competitors to traditional signal processing algorithms. Thus, we will also investigate approaches to mitigate the interference and retain the information of the signal that can be further processed in the spiking domain. One important step is the detection of the exact time of interference, as it was already observed with readout neurons with a smaller membrane time constant.

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