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Spectral Attention-Driven Intelligent Target Signal Identification on a Wideband Spectrum

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Outline

- Introduction and Motivations
- Problem Settings
- Proposed Method
  - SCF-based Feature Visualization
  - Spectral Attention-Driven Detection Mechanism
- Simulation Results
- Conclusions

Introduction and Motivations

- Cognitive Radio (CR) has been widely adopted to address the growing scarcity of electromagnetic spectrum for radio frequency (RF) communication [1]–[3].
  - Machine learning techniques have provided promising solutions in both wideband and narrowband spectrum sensing and other radio frequency signals related applications [6]–[8].
- A major challenge for machine learning based wideband spectrum sensing applications in CR is that feature visualization method such as Spectral Correlation Function (SCF) on the wideband can be computationally expensive.
  - Efficiently identifying correlated features for the targeted spectrum-sensing tasks is necessary to achieve an effective tradeoff between the low computational complexity and the high decision-making accuracy.

Problem Settings

- We focus on developing a spectral attention-driven reinforcement learning-based intelligent method for effective and efficient detection of important signals in a wideband spectrum.
  - As the first stage to achieve this goal, in this paper we assume that the modulation technique used is available as a prior knowledge of the targeted important signal.
  - While the receiver has the knowledge of the modulation scheme of the target signal,
    - ✓ It does not have the information of the carrier frequency.
    - ✓ There may exists frequency-hopping spread spectrum depending on the opportunistic channel selection of the CR transmitter.

Problem Settings

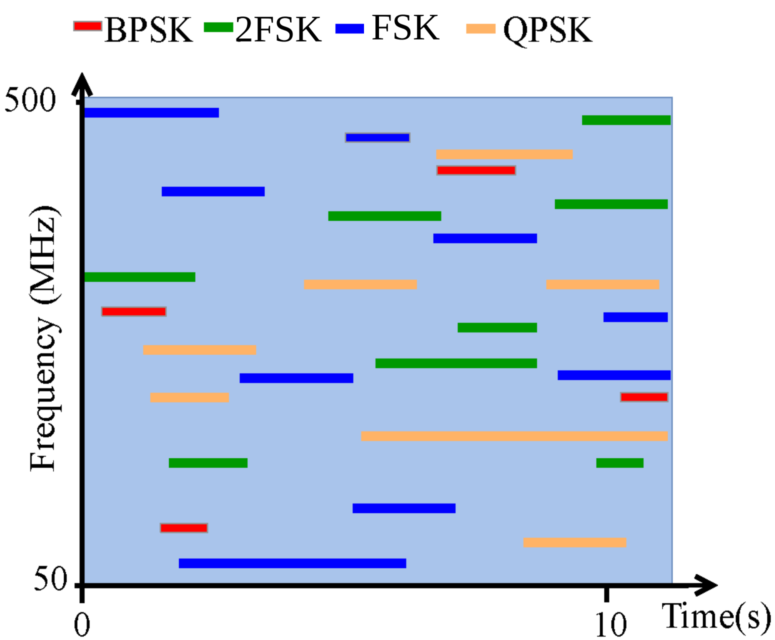


Fig. 1: Spectrum with target signal among other signals.

- As an example, consider the frequency-time spectrum of a wideband background signal that contains 2FSK, 4FSK, and QPSK-modulated signals within a random bandwidth ranging between 50 and 500 MHz.
- Our task is to detect a target signal whose modulation technique, BPSK is known as a priori knowledge.

Proposed Method

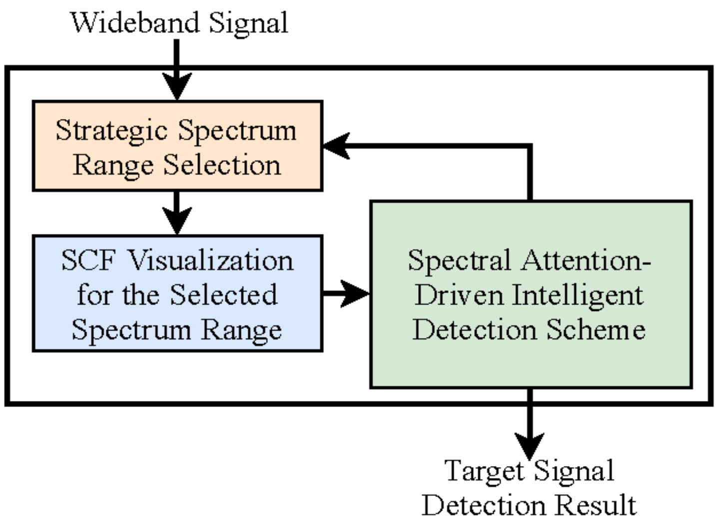


Fig. 2: Overview of our proposed method.

- Our proposed spectral attention-driven reinforcement learning-based intelligent method mainly comprises:
  - SCF-based Feature Visualization
  - Spectral Attention-Driven Detection Mechanism

Proposed Method

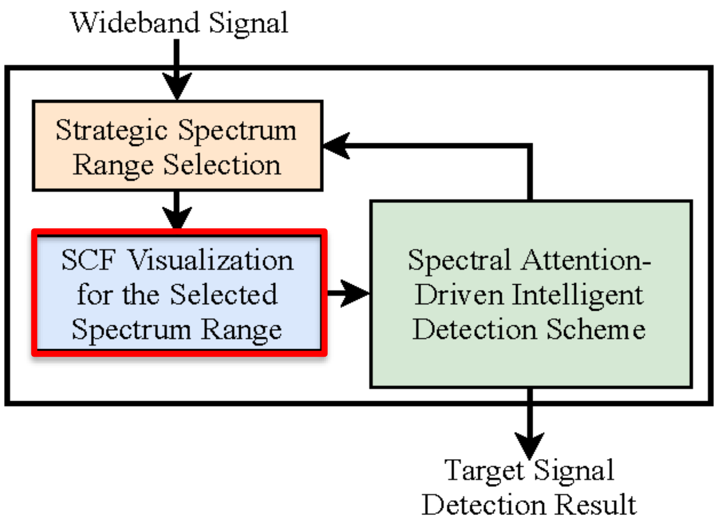


Fig. 2: Overview of our proposed method.

- We employ the SCF to pre-process the received RF signals and to visualize the observed spectrum environment.
  - The output of our SCF-based visualization method is a 2-D image that characterizes the features associated with all the received signals.
  - The features presented by the 2-D image associated with different spectrum ranges do not have equal values for contributing to the target signal detection.

Proposed Method

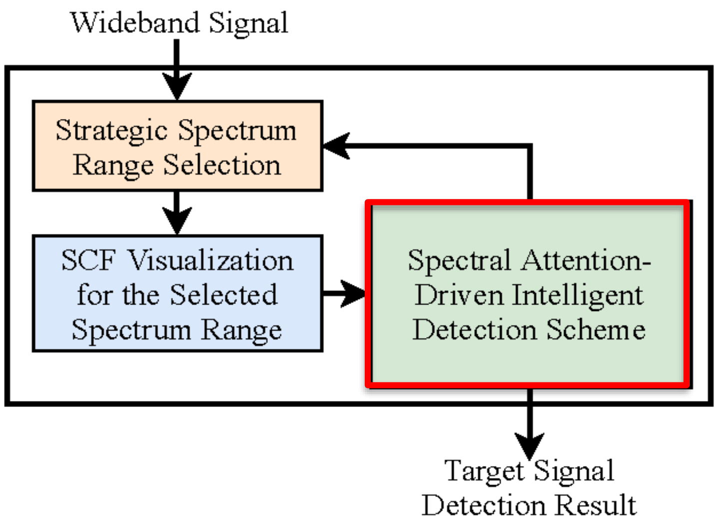


Fig. 2: Overview of our proposed method.

- We exploit the reinforcement learning and deep learning techniques to develop a spectral attention-driven intelligent detection scheme.
  - To adaptively identify the critical spectrum range whose features presented by the 2-D image
  - To selectively integrate the critical features of the selected spectrum range to achieve the signal detection.

Proposed Method: SCF-based Feature Visualization

- The modulated signals are treated as cyclostationary processes that refer to the processes with periodic statistics, such as mean and autocorrelation.
- Spectral correlation function (SCF) $S_x^\alpha[f]$ is formulated by implementing Fourier transform on cyclic auto-correlation function (CAF) $R_x^\alpha[l]$ that calculates the amount of correlation between different frequency shifted versions of a given signal and represents the fundamental parameters of their second order periodicity.
  - $$\begin{cases} S_x^\alpha[f] = \sum_{l=-\infty}^{\infty} R_x^\alpha[l] e^{-j2\pi f l} & (1) \\ R_x^\alpha[l] = \left[\lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x[n]x^*[n-l]e^{-j2\pi\alpha n}\right] e^{-j\pi\alpha l} & (2) \end{cases}$$

where f denotes the digital temporal frequency of the modulated signal, and $\alpha = m/T_0$ be the cyclic frequency that indicates the cyclic evolution of the waveforms where m is an integer and T_0 is the process period.

Proposed Method: SCF-based Feature Visualization

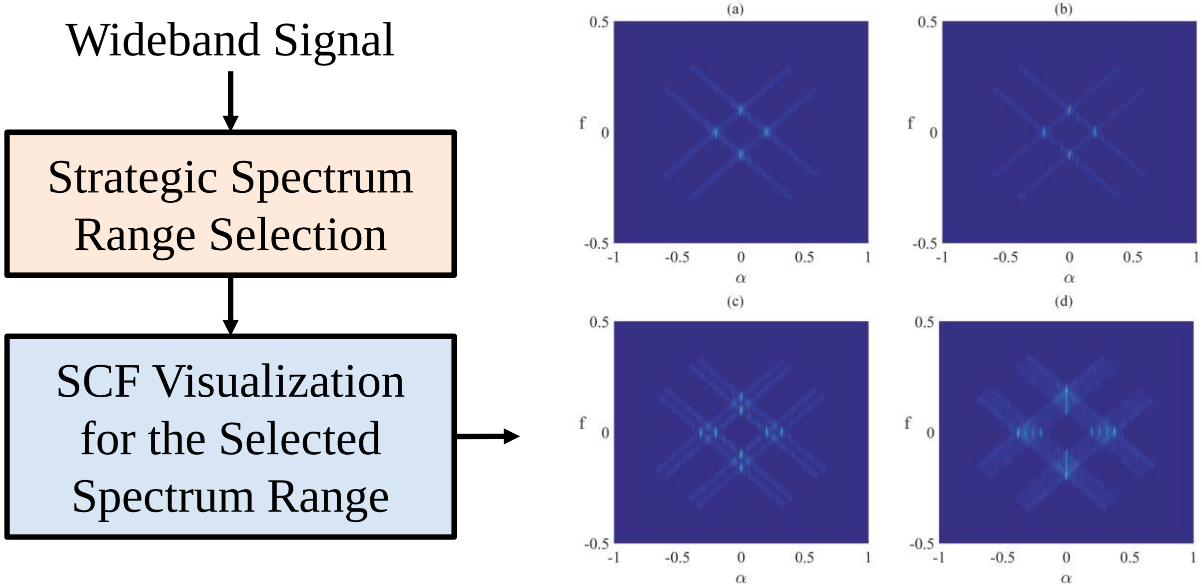


Fig. 3: Top view of the SCF patterns of (a) BPSK; (b) QPSK; (c) 2FSK; and (d) 4FSK modulation schemes: lighter color intensity represents higher value.

- The 2-D SCF patterns can be obtained by calculating Eq. (1) for different values of α and f.
- Each pixel intensity of the 2-D image represents the SCF value for the corresponding digital temporal frequency and cyclic frequency.

Spectral Attention-Driven Detection Mechanism

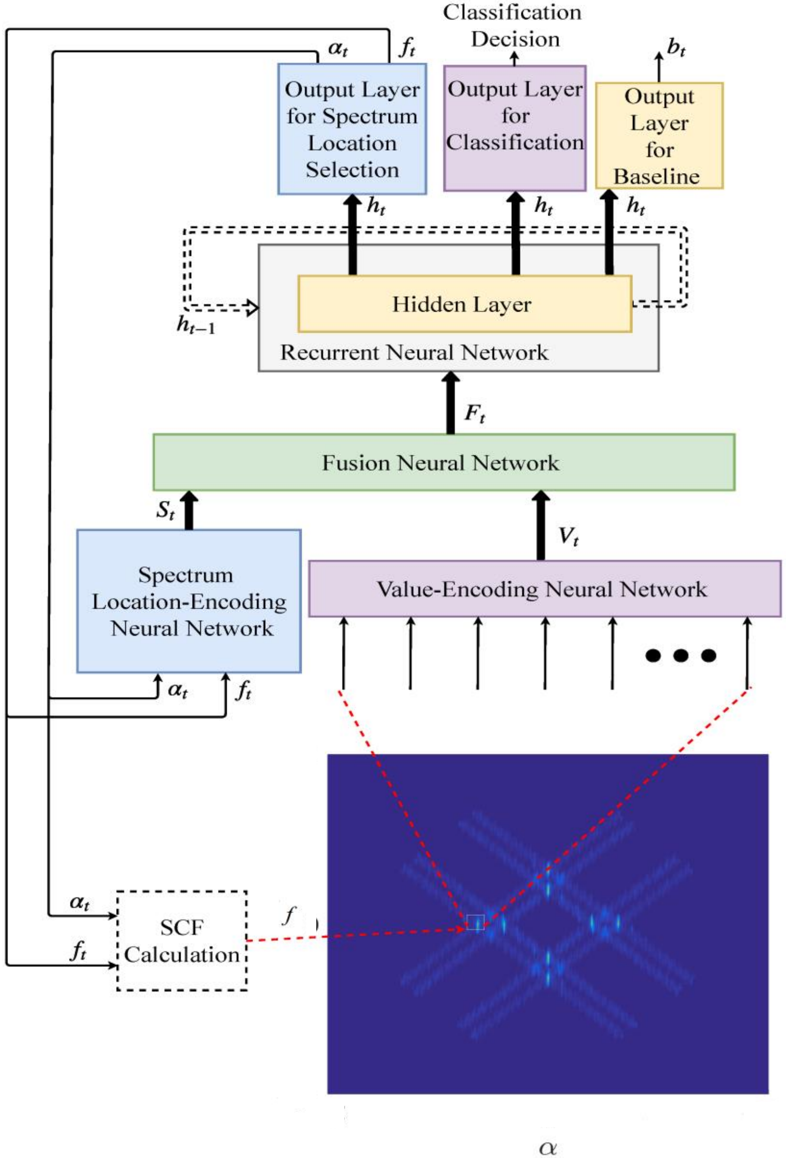
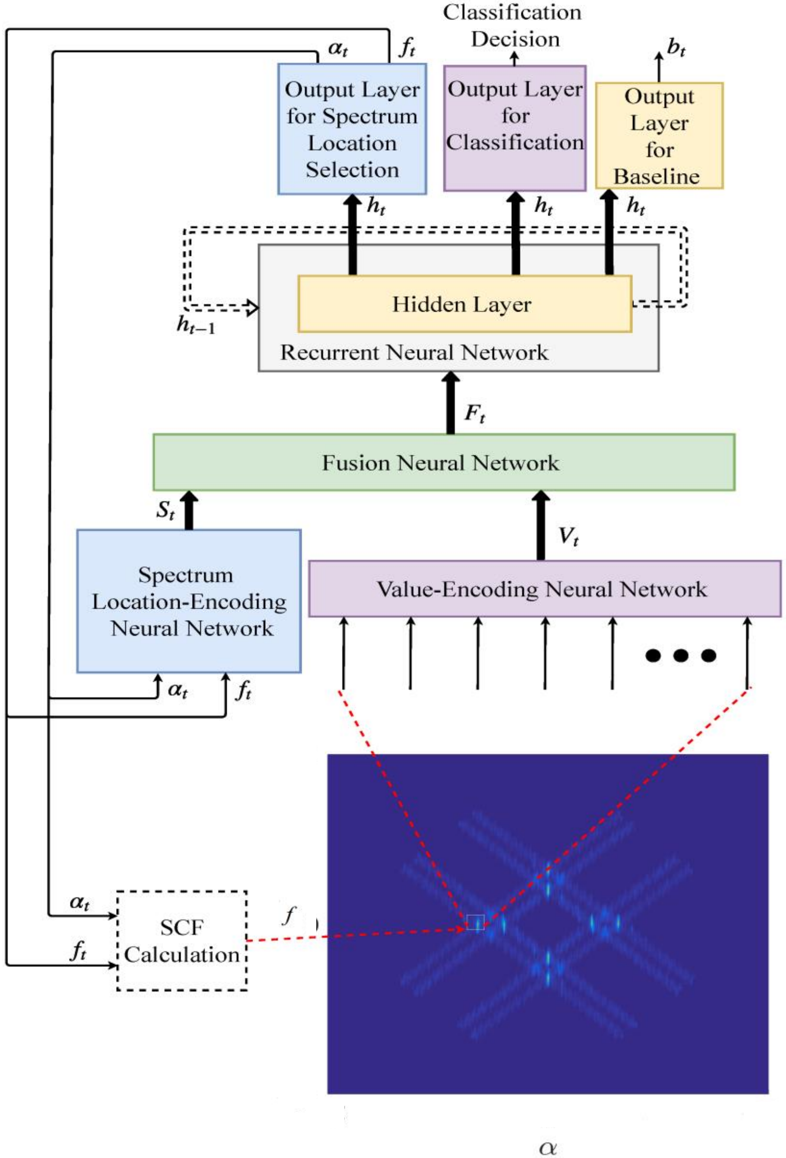


Fig.4: Reinforcement learning-based spectral attention-driven method.

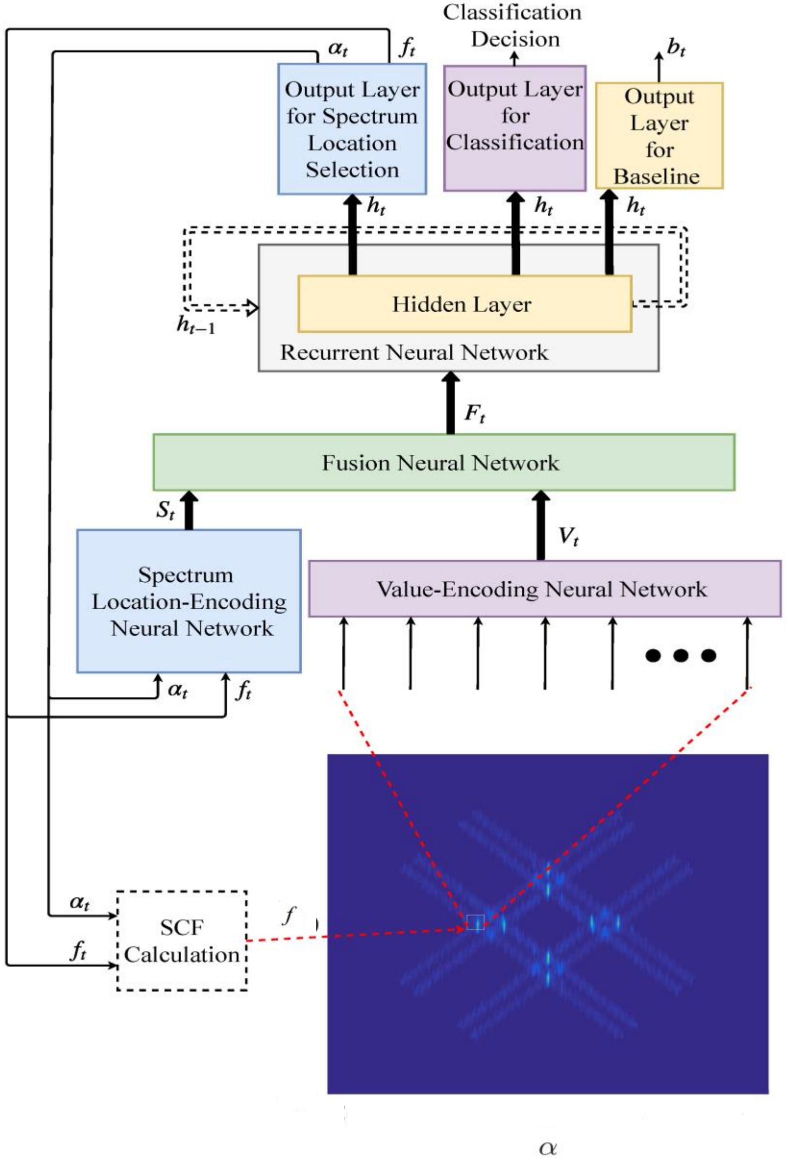
Spectral Attention-Driven Detection Mechanism



- The output of the SCF-based method is only a small patch that is defined by the center temporal frequency f_t and center cyclic frequency α_t at time t, of the 2-D image that is potentially generated using the signals received across the wideband spectrum.
- The selected spectrum (f_t, α_t) is called spectral attention in our work and the decision on the spectral attention is made adaptively by using our spectral attention-driven method.

Fig.4: Reinforcement learning-based spectral attention-driven method.

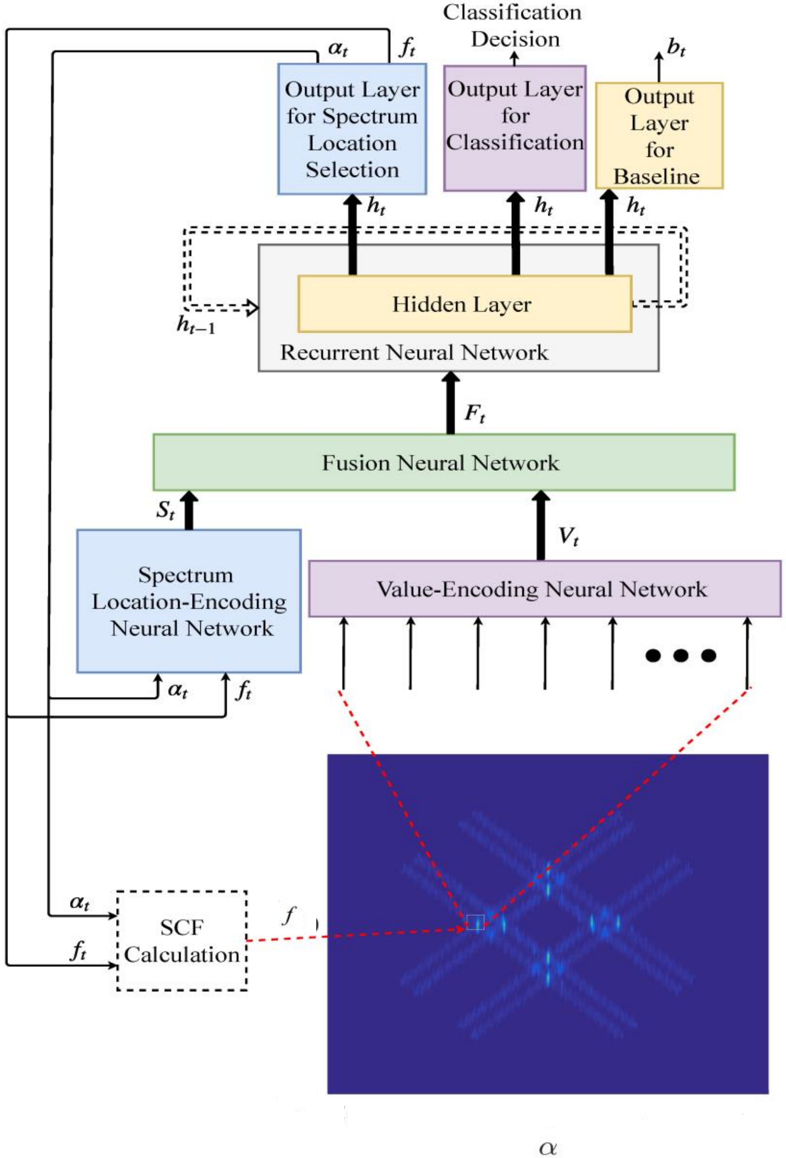
Spectral Attention-Driven Detection Mechanism



- The SCF-based visualization output of the signals observed in the previously selected spectrum is reshaped as a vector and fed into the value-encoding neural network that generates the encoding for value $\mathbf{V}_t$.
- A spectrum location-encoding neural network generates the representation S_t for the spectrum location (f_t, α_t).
- The fusion neural network (NN) is used to generate a fused representation $\mathbf{F}_t$ of $\mathbf{V}_t$ and $\mathbf{S}_t$.

Fig.4: Reinforcement learning-based spectral attention-driven method.

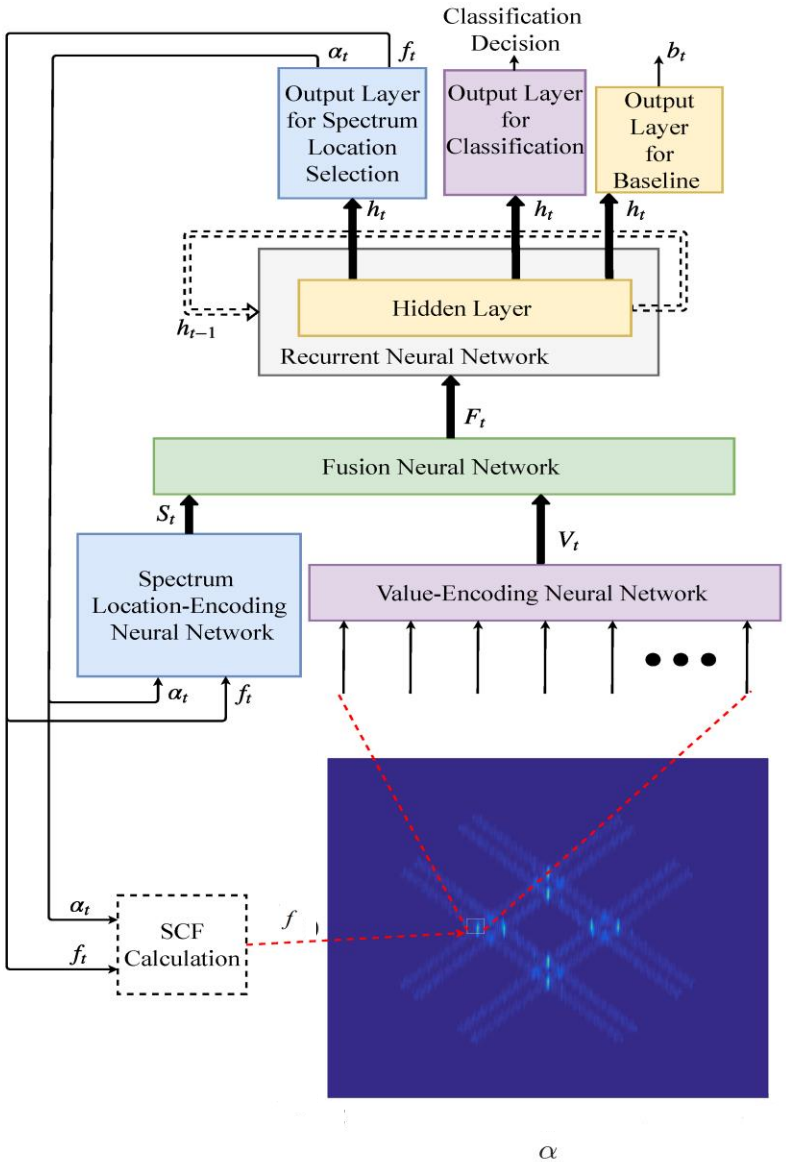
Spectral Attention-Driven Detection Mechanism



- A recurrent neural network (RNN) is designed to characterize temporal features embedded in F_t.
  - The RNN has one hidden layer that is denoted by $\mathbf{h}_t$ for time t.
  - The hidden layer is generated via a NN structure using the previous time-step value of hidden layer $\mathbf{h}_{t-1}$ and $\mathbf{F}_t$ as inputs.

Fig.4: Reinforcement learning-based spectral attention-driven method.

Spectral Attention-Driven Detection Mechanism



- The hidden layer of the RNN, $\mathbf{h}_t$, is considered as the input for three NNs, (1) Spectrum Location Selection NN that generates the spectrum location for the next time-step (f_{t+1}, α_{t+1}), (2) Classification NN that obtains the binary detection decision on spectrum sensing, and (3) baseline NN that calculates the baseline b_t for formulating our reinforcement learning (RL)-based training procedure.

Fig.4: Reinforcement learning-based spectral attention-driven method.

Spectral Attention-Driven Detection Mechanism

- We model our spectral attention-driven target as a partially observable Markov decision process (POMDP) and optimize the process adaptively via a policy gradient-based reinforcement learning method.
  - The state vector $\mathbf{s}_t$ is defined by the hidden layer of the RNN $\mathbf{h}_t$ that summarizes the information extracted from the history of past observations.
  - The action vector $\mathbf{a}_t$ is defined by using the spectrum location $\{f_t, \alpha_t\}$ and the binary detection outputs of the neural network structure.
  - The cumulative reward R is defined as $R = \sum_{t=1}^{T} r_t$, where

$$r_t = \begin{cases} 1 \text{ if classification decision is correct at } t = T \\ 0 \text{ otherwise} \end{cases}$$

Spectral Attention-Driven Detection Mechanism

- Our spectral attention-driven method is optimized adaptively using a policy gradient-based reinforcement learning method.
  - The gradient of the total expected reward can be approximated as follows: $\nabla_\theta J(\theta) \approx \frac{1}{MT}\sum_{i=1}^{M}\sum_{t=1}^{T}\nabla_\theta \ln \pi_\theta(\mathbf{a}_t|\mathbf{s}_{1:T})\left(R_t^i - b_t\right)$, where M is the Monte Carlo sampling number.
  - A loss function L is defined considering reward maximization and reducing the classification error.
    $\nabla_\theta L = -\nabla_\theta J(\theta) + \frac{1}{M}\nabla_\theta\left\{\sum_{i=1}^{M}(y_i - \bar{y})\right\}$, where
    y_i is the actual label and $\bar{y}$ is the predicted label in the Tth time step.
  - The parameter set is updated iteratively based on the gradient-descent update rule: $\theta_{n+1} = \theta_n - \alpha\nabla_\theta L$, where α is the learning rate and n is the index of the training trials.

Spectral Attention-Driven Detection Mechanism

- Our spectral attention-driven method is optimized adaptively using a policy gradient-based reinforcement learning method.
  - While training, the network is expected to learn a policy to decide what locations on the spectrum to look at to make a reliable classification decision at the timestep T. This will reduce the computation cost of calculating SCF on a wide bandwidth.

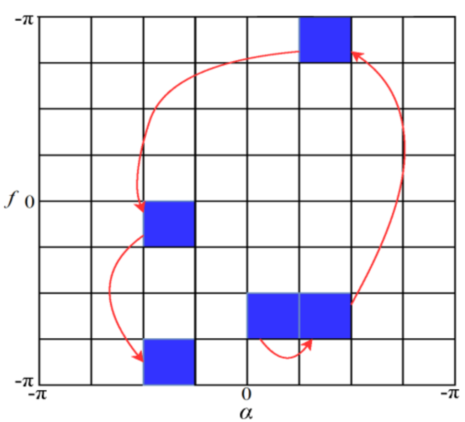


Fig.5: Example of the reduced SCF pattern calculation for the proposed 5-step attention-based method.

- ✓ The full grid represents the whole temporal and cyclic spectrum considered.
- ✓ The parts in blue are where SCF-based 2D pattern calculated for the machine learning-based spectrum sensing.
- ✓ The arrows show the transition of focus for the 5 steps attention-based method.
- ✓ Therefore, only 5 out of 64 of SCF calculation is needed to for the proposed attention-based method, which is a large reduction in computation cost.

Simulation Results

- In the simulations, we consider the frequency-time spectrum of a wideband background signal consisting of 2FSK, 4FSK, and QPSK-modulated signals within a random bandwidth ranging between 50 and 500 MHz and a BPSK-modulated target signal.
- The objective of the simulations is to detect the BPSK-modulated target signal.

TABLE 1: PARAMETERS OF THE SPECTRAL ATTENTION-DRIVEN METHODS USED IN THE SIMULATIONS

Parameter	Vector Dimensions
Input	16
Time-steps (T)	5
Encoding for value (V_t)	128
Encoding for spectrum location (S_t)	128
Fused representation (F_t)	256
Hidden layer (h_t)	256
Spectrum location output	2
Classification output	1

Simulation Results: Scenario I

- In this scenario, we assume that there is only one of the BPSK, QPSK, 2FSK, and 4FSK-modulated signals is present at the receiver in the considered time window.
- The carrier of the modulated signal is randomly selected from 100 MHz, 200 MHz, 300 MHz, and 400 MHz.
- For all considered carrier frequencies, the detection accuracy remained above 93% for this scenario.

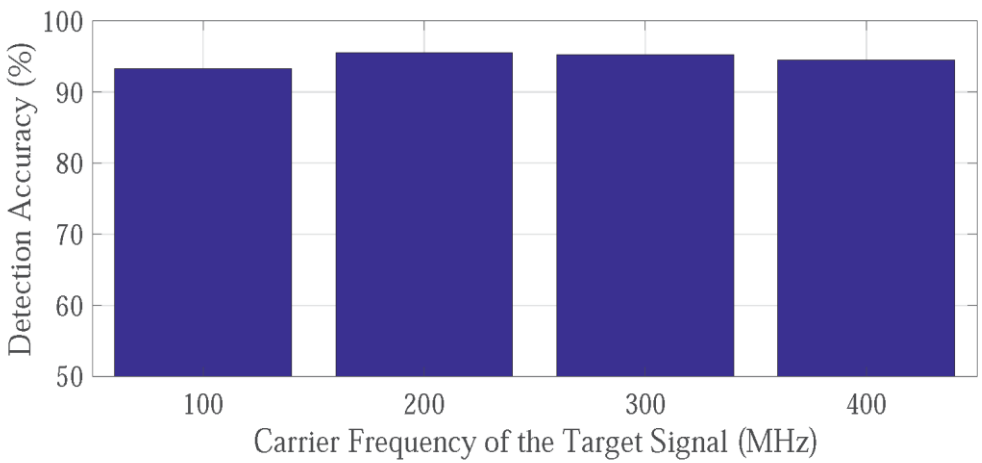


Fig.6: Detection accuracy of the target BPSK signal in Scenario I.

Scenario II

- In this scenario, we consider a background with one, two, or none of QPSK, 2FSK, 4FSK-modulated signals and the target BPSK-modulated signals are present in some of the received time windows.
- The detection accuracy obtained using our proposed attention-driven method is comparable with the accuracy using a regular two-layer convolutional neural network (CNN) with full spectrum input.

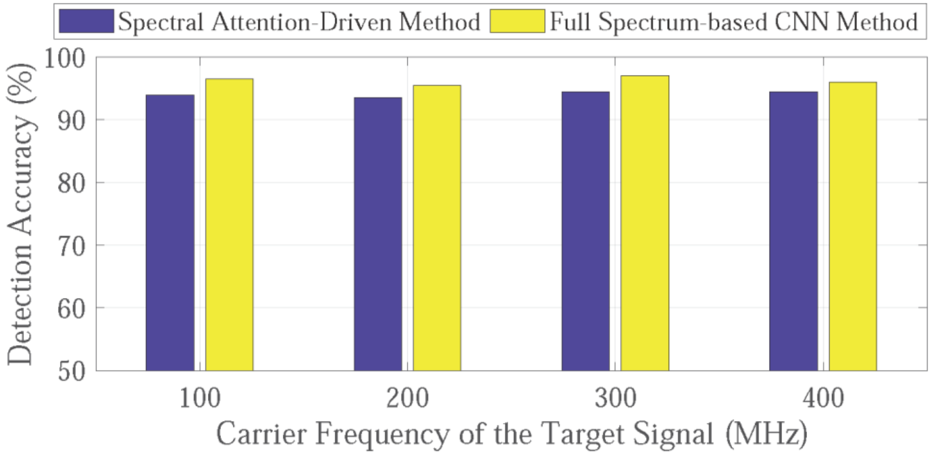


Fig.7: Detection accuracy of the target BPSK signal in Scenario II.

Conclusions

- In this paper we present our initial work on developing a bio-inspired spectral attention-driven method for effectively detecting an event-driven target signals in a wideband spectrum.
- Our spectral attention-driven method proposed in this paper consists of two main components: a SCF-based spectral visualization scheme and a spectral attention-driven mechanism that adaptively selects the spectrum range and implements the intelligent signal detection.
- As illustrated in the simulation results, our proposed method can achieve high accuracy of signal detection via effectively selecting the spectrum range to be observed.
  - Achieving a good tradeoff between a high accuracy and low computation cost.
- We believe that our proposed spectral attention-based method can lead to an efficient adaptive intelligent spectrum sensor designs in cognitive radio (CR) receivers.

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Thank You!
Questions?

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