

AI-Driven Self-Optimizing Receivers for Cognitive Radio Networks

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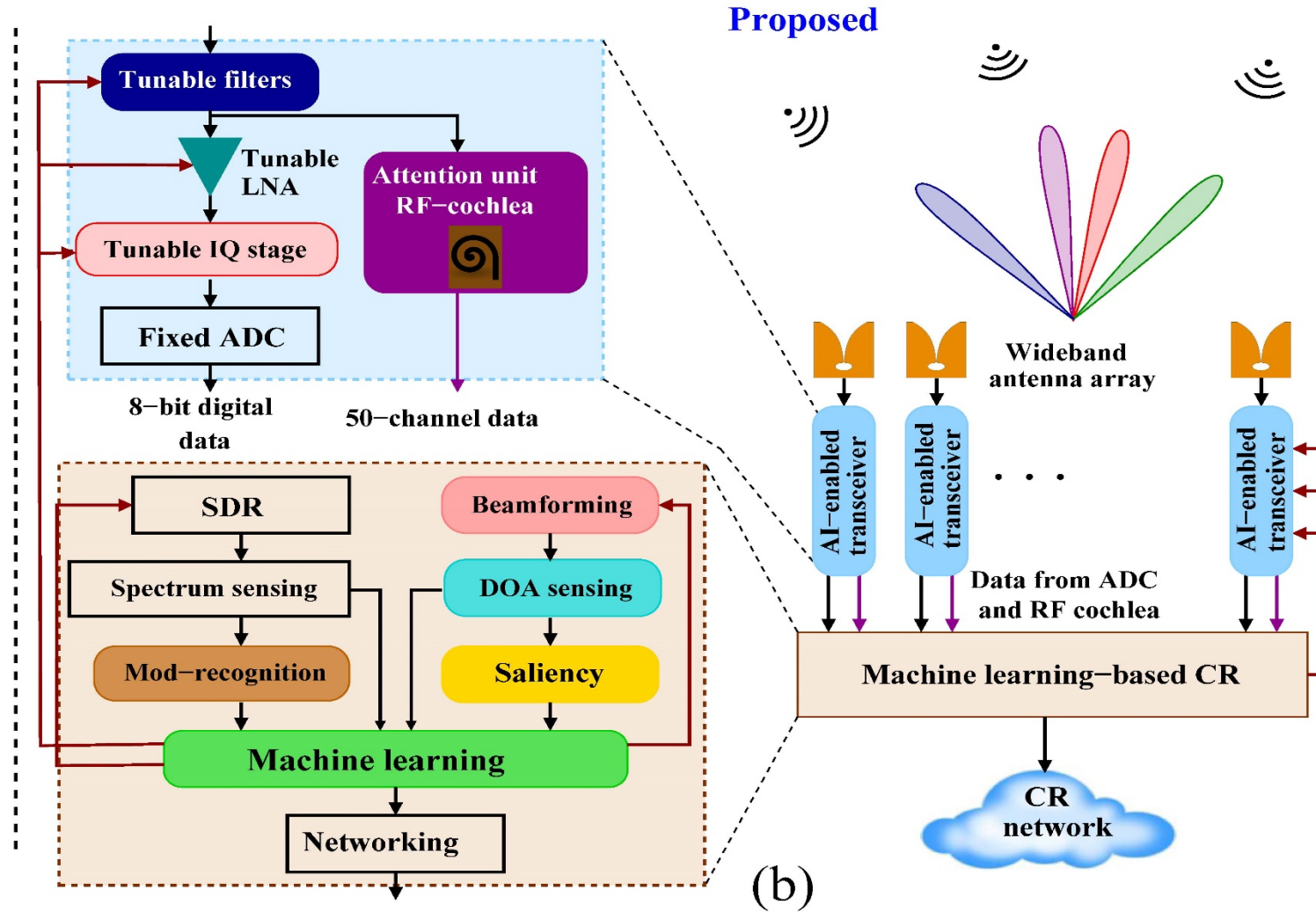
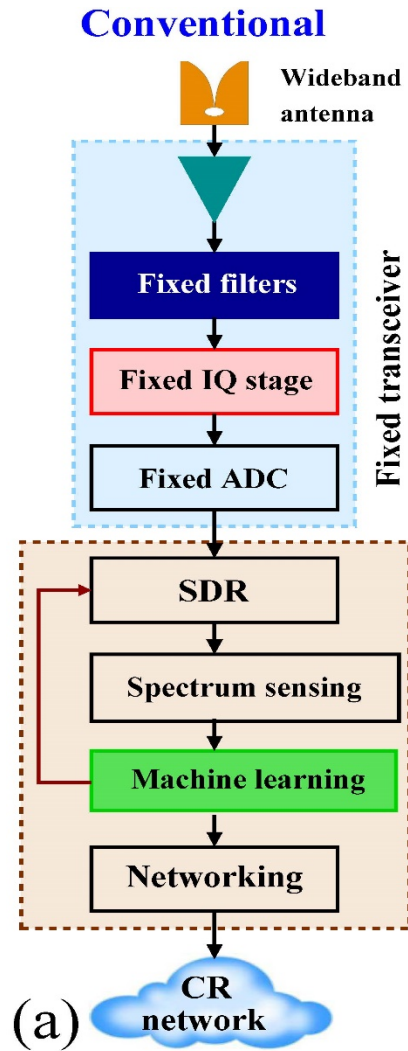
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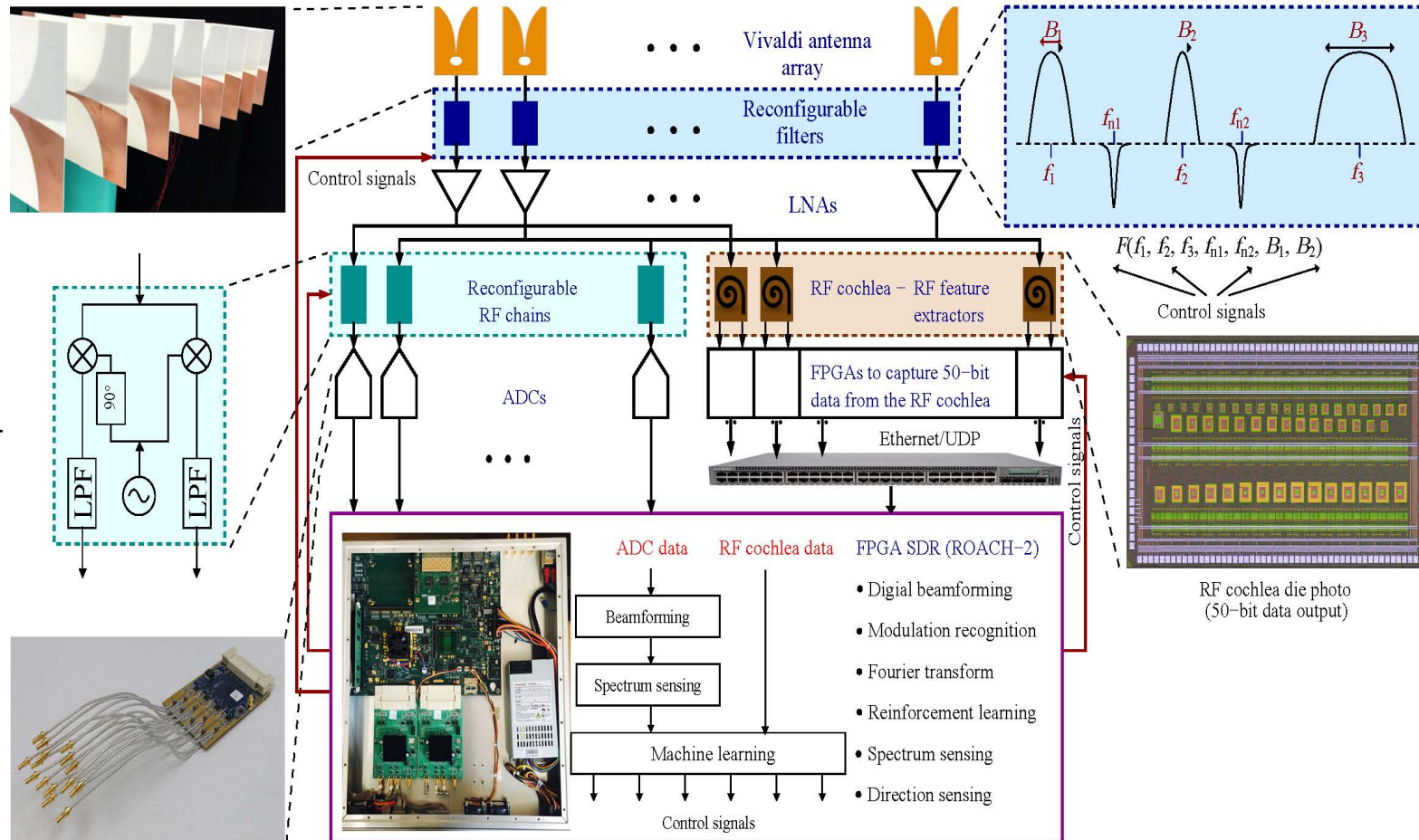


Introduction



The AI-enabled architecture encompasses directional spectrum sensing and modulation recognition with attention and saliency to close the loop on agile RF and software-defined radio (SDR) hardware that adapts to changing RF scenes.

Proposed AI-enabled CR receiver architecture block diagram



- The 1st path combines data from the two sets of signal paths to generate CR-relevant information.

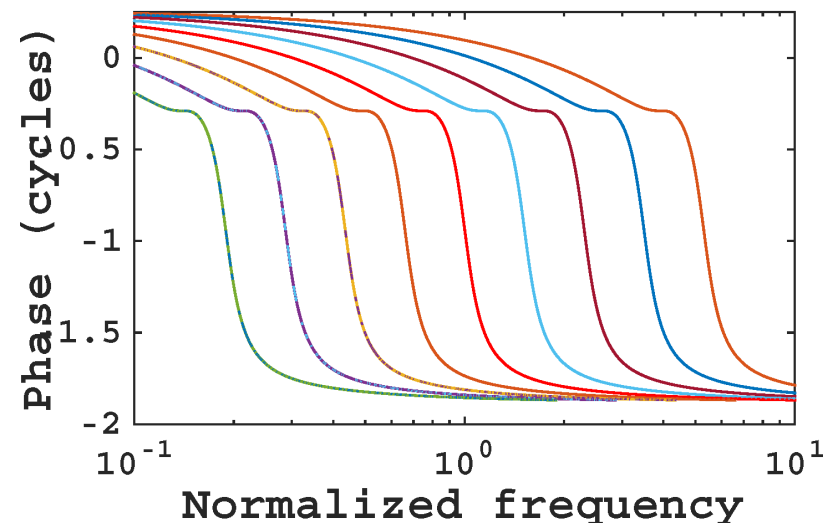
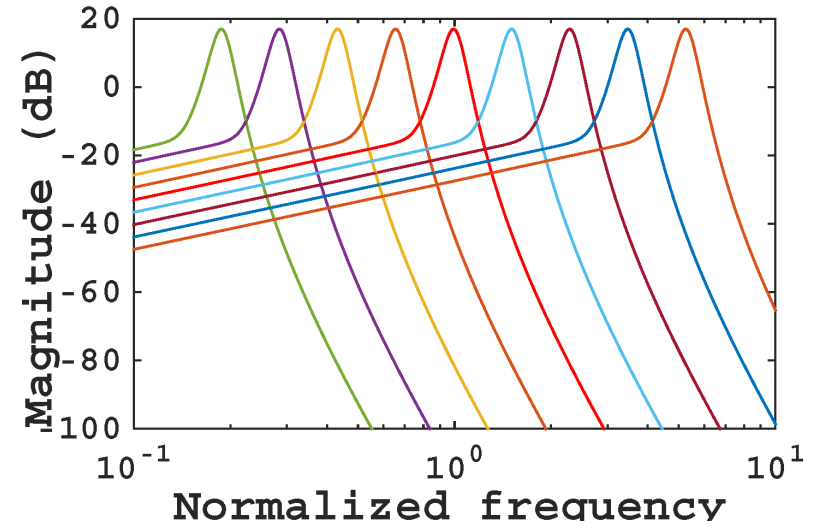
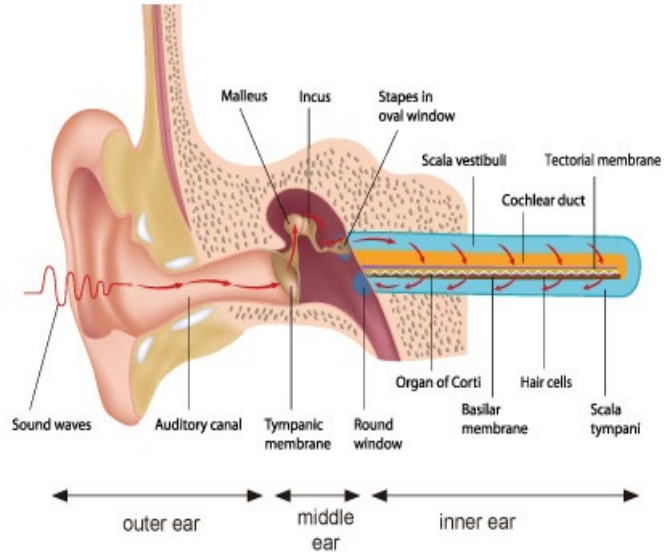
- The 2nd path uses bio-inspired real-time spectrum analysis chips (known as “RF cochleas”) to extract digitized time-frequency features that provide spectrum awareness over several GHz of real-time bandwidth.
- Low-power FPGAs packetize these N parallel sets of features and then feed them into a high-bandwidth reconfigurable processor (e.g., ROACH-2 platform)

- It determines spatio-temporal activity levels to select data for further analysis;
- It performs RF scene analysis on the selected data to localize important sources and recognize their modulation protocols.

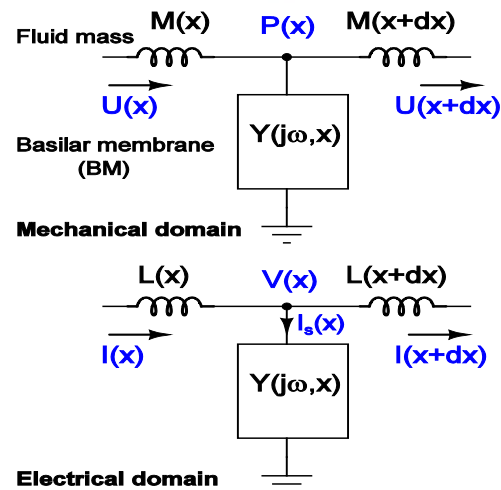
Cochlea – Introduction

Anatomy of human ear

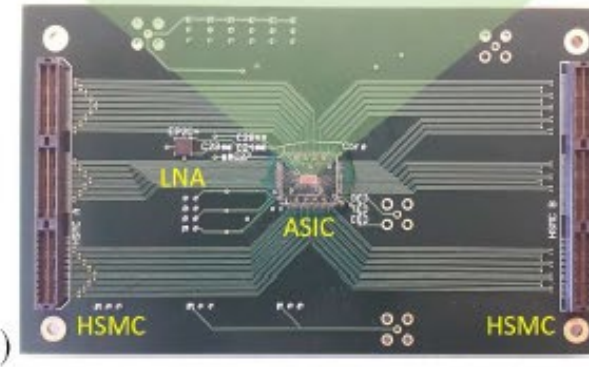
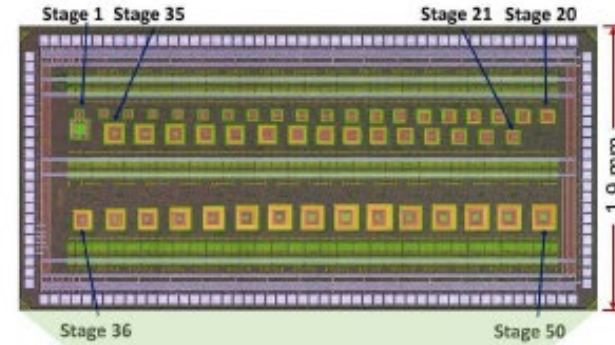
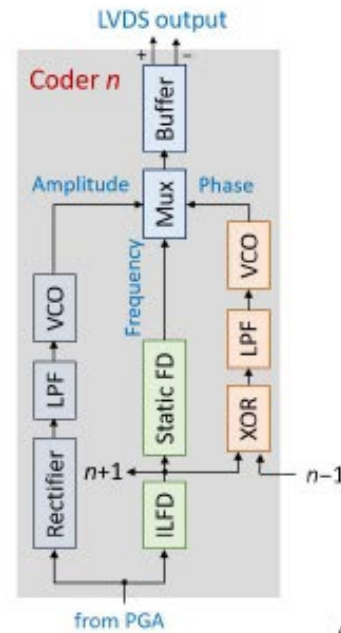
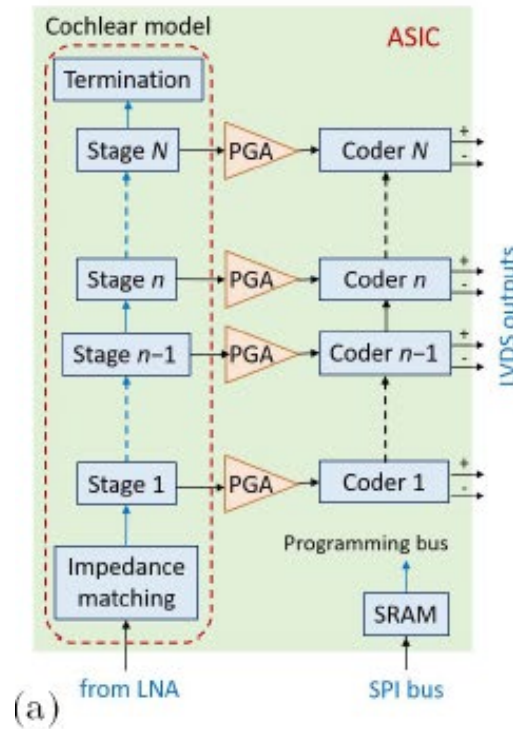
- Dynamic range (at input): 120 dB
- Power consumption: $\sim 14 \mu\text{W}$
- Frequency range: 20 Hz \sim 20 KHz



A generic spatially-varying one-dimensional transmission line



Cochlea – Block diagram



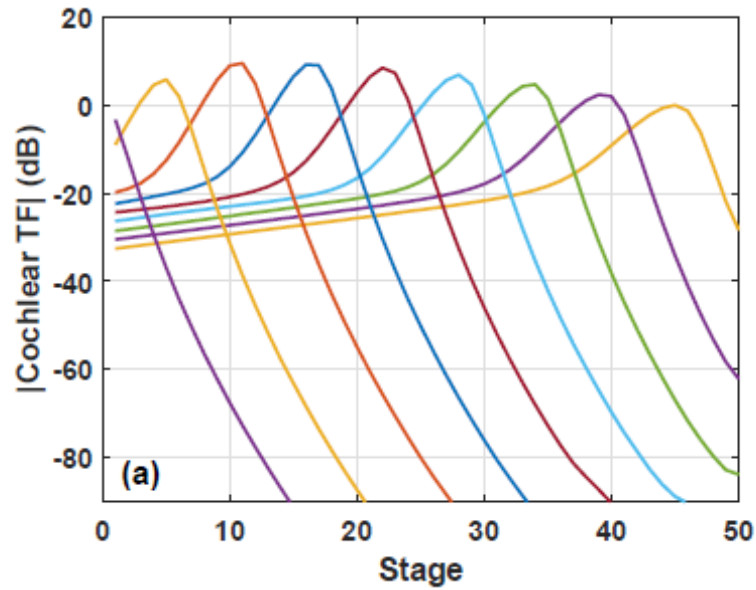
Performance summary

Parameter	Value
Technology	UMC 65 nm CMOS
Dimensions	3.95 mm x 1.88 mm
Power supply voltage	2.5 V and 1.2 V
Power consumption	530 mW
Frequency range	0.8 GHz - 8.4 GHz
Cochlear stages	50
Programmable bits/stage	20
Digital output channels	45
Output latency	~5 RF cycles
Output data rate	~25 Msps/channel
Output resolution	5-7 bits

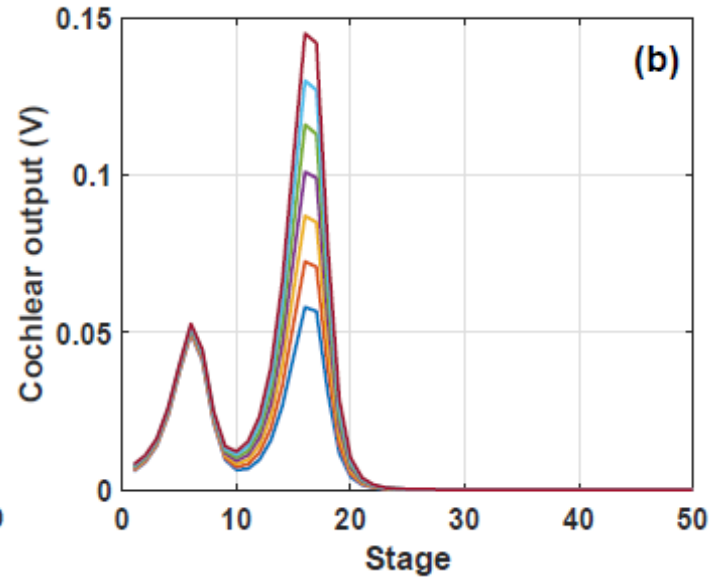
Simplified block diagram of the proposed cochlea-based ultra-broadband RF feature extractor.

Photograph of the digitally-programmable RF cochlea chip superposed on its test board, while directly plugs into an FPGA back-end via two high-speed mezzanine card (HSMC) connectors.

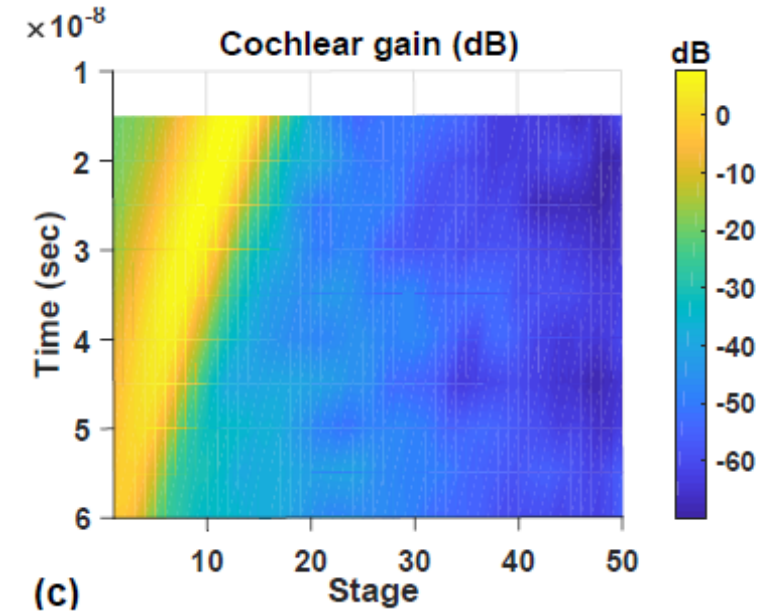
Cochlea – Typical outputs



Spatial TFs for continuous wave (CW) inputs at log-spaced input frequencies (1.5~10.0 GHz).

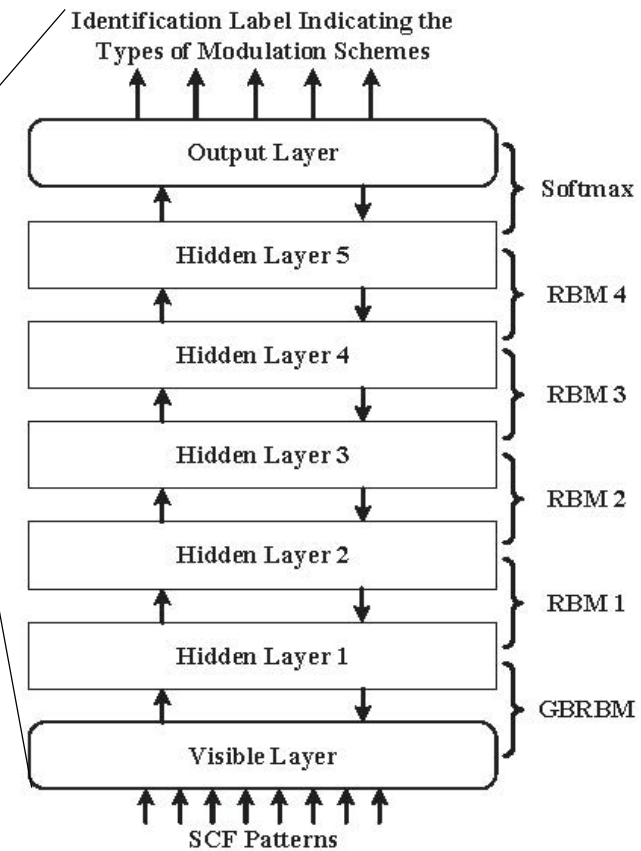
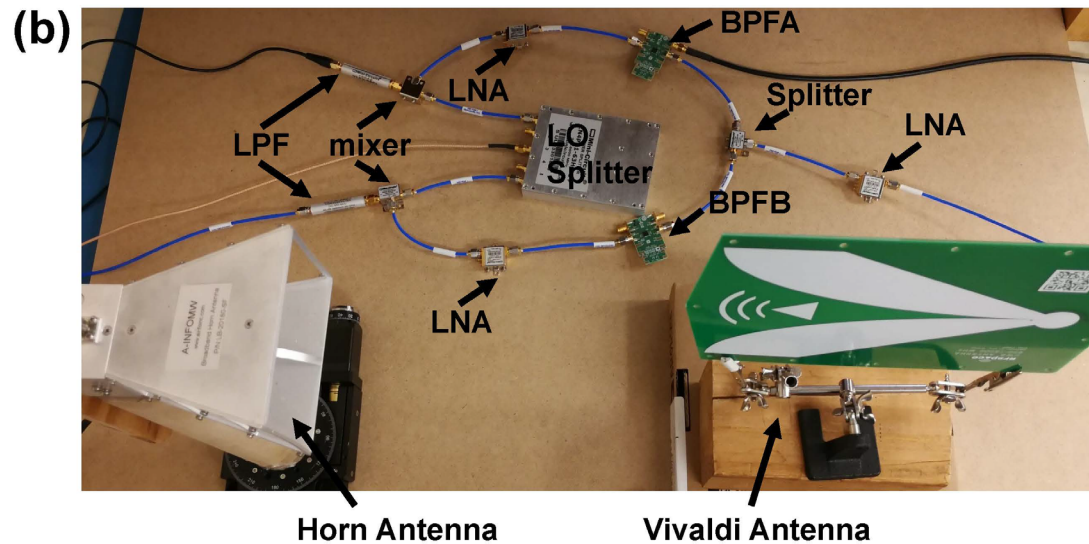
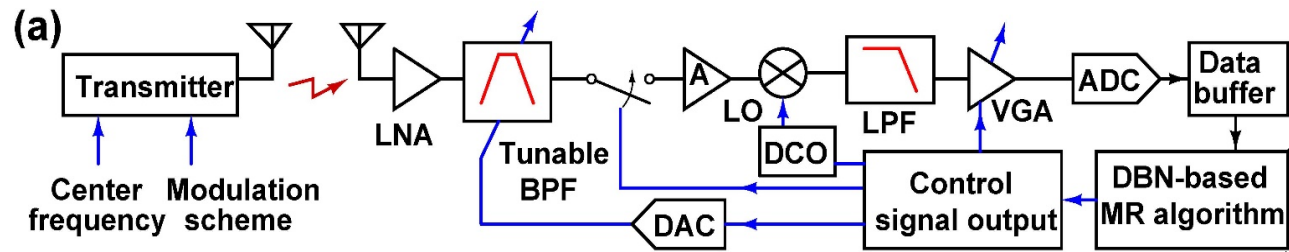


Spatial output responses for an RF input contains two CW frequencies: 7.5 GHz (amplitude = 20 mV) and 5 GHz (amplitude varying from 20~50 mV in 5 mV steps).



Time-varying spatial output response to a chirp input (frequency linearly increasing from 5 to 6.5 GHz in 60 ns).

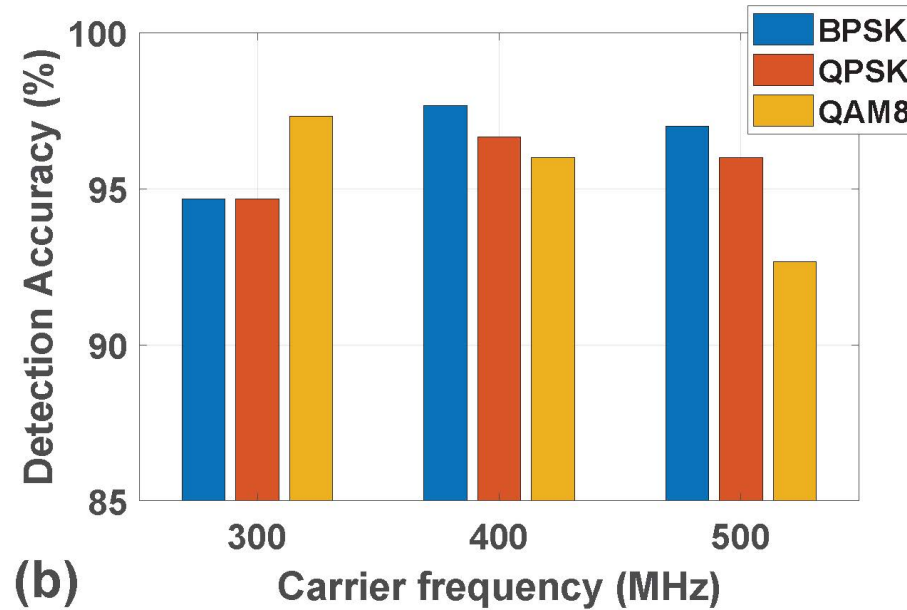
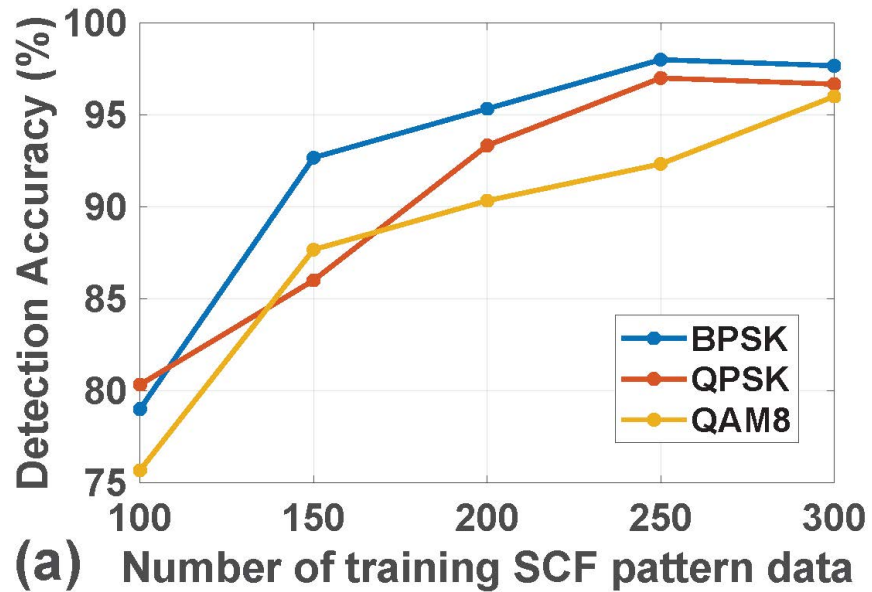
Experimental setup



- Second-order features unique to each modulation scheme can be extracted from its spectral correlation function (SCF) while suppressing stationary features.
- A deep learning-based classifier is leveraged to recognize the unique features of such visualized SCF patterns to identify the observed RF signal.

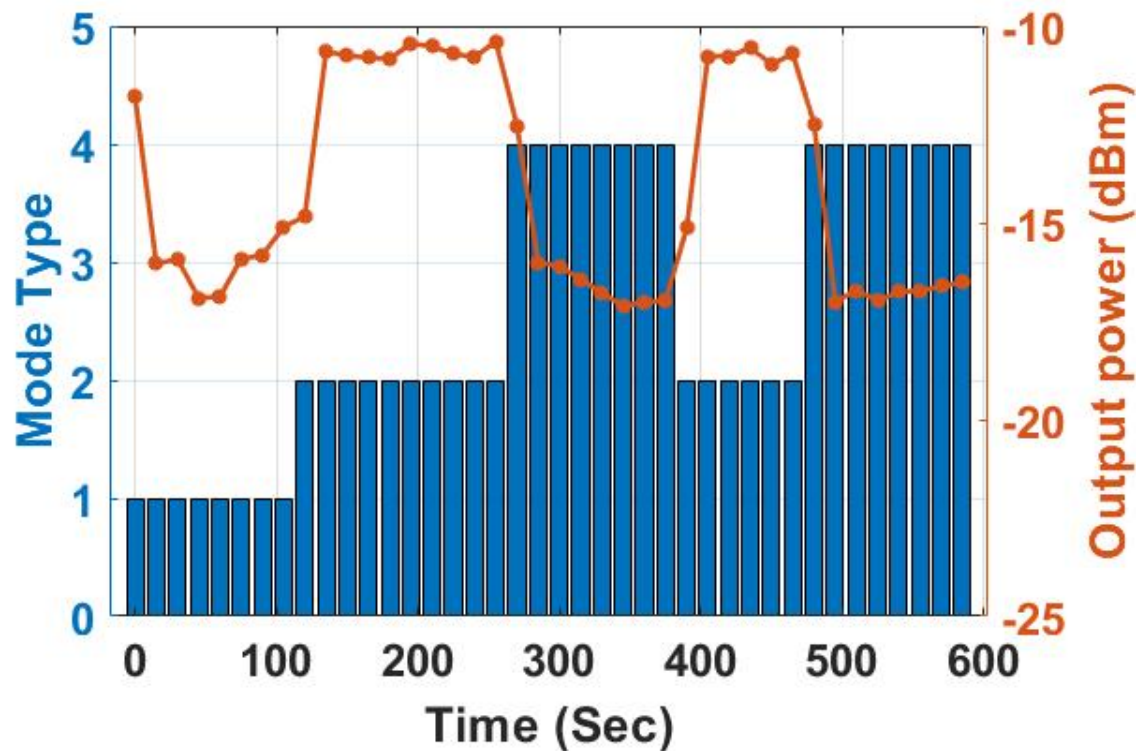
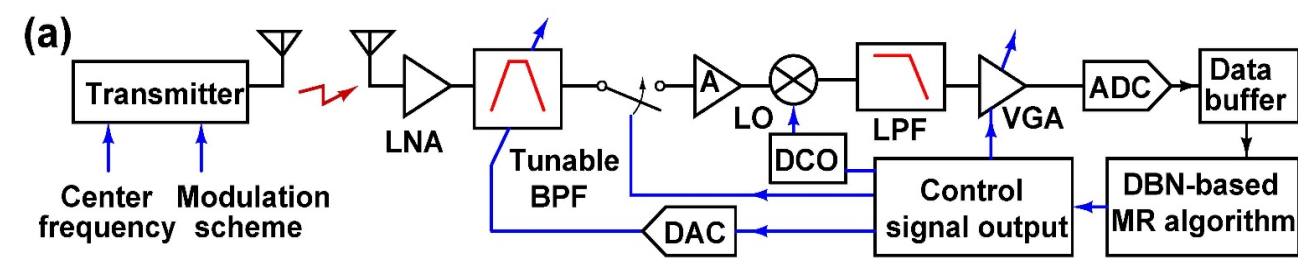
(G. Mendis, J. Wei, and A. Madanayake, "Deep belief network for automated modulation classification in cognitive radio," in IEEE Cognitive Communications for Aerospace Applications Workshop (CCAA), 2017.)

Experimental MR accuracy



- An obvious improvement exists as the size of the training set increases; it remains > 90% when this number is >200.
- Detection accuracy after training the network with 300 SCF patterns was > 92.5% in all cases.

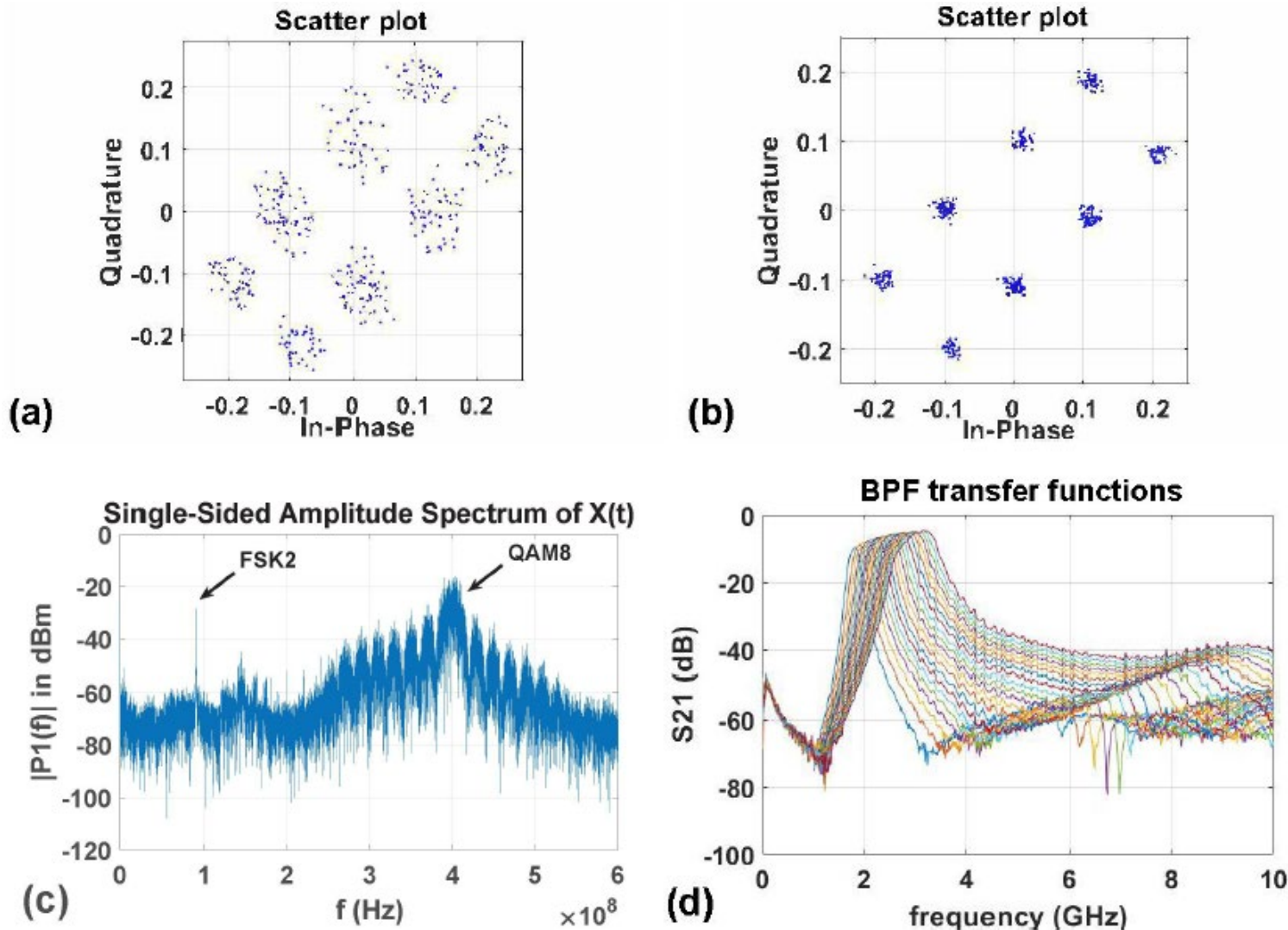
MR-enabled iterative optimization



MR enables iterative optimization of the RF receiver when the latter lacks **priori** knowledge of the expected signal parameters. In particular, we can use ML-based MR to continuously adapt a CR to optimally receive the desired wireless signals.

- 1) A 3 GHz RF transmitter is programmed to randomly select one of three modulation schemes (1=BPSK, 2=QPSK, and 4=QAM8) and the receiver output is recorded at each time step (15 sec).
- 2) A trained DBN network classifies the down-converted signal.
- 3) A controller (implemented in MATLAB) tunes an RF band-pass filter (BPF) to maximize signal gain if the desired scheme (in this case, QPSK) is detected, or else de-tunes it to reduce gain and prevent blocking.
- 4) Loop bandwidth is limited by the software-based ML implementation and can be greatly improved by using an FPGA instead.

MR-enabled blocker removal



The proposed ML-based MR can also be used to adaptively remove undesired wireless signals (blockers).

- 1) Two modulated signals (QAM8 at 3 GHz, and FSK2 at 2.7 GHz) with the same power level.
- 2) The RF receiver sweeps the BPF control voltages and optimizes the BPF to maximize signal gain when the desired scheme (QAM8) is detected by the trained DBN.
- 3) A significant improvement in the received constellation after optimization, with the blocker being suppressed by ~ 10 dB
- 4) Given the limited selectivity of the tunable BPF, the proposed approach is only effective for removing far-out blockers (>250 MHz away from the desired signal).

Conclusion

The proposed AI-driven spectrum awareness approach enables:

- i) A CR receiver's RF front-end to be autonomously optimized for receiving a given set of waveforms;
- ii) DSA algorithms that detect and exploit spatio-temporal white space on various timescales by closely integrating the adaptive front-end with MR algorithms.

A single-channel prototype operating around 3 GHz has been implemented and tested. Experimental results show:

- i) > 90% over-the-air MR accuracy for several common schemes using a DBN;
- ii) Autonomous self-optimization of the tunable RF front-end.

Future work:

- 1) Multi-channel platform operating on broadband input signals;
- 2) RF cochlea output integrated with the MR algorithms.

Thank you for your attention

