High-Speed Sensing of the Electromagnetic (EM) Environment for Cognitive Radio Receivers

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ABSTRACT

In this paper we demonstrate an EM environment aware (EMEA) radio called the Intelligent Transceiver Radio Node (ITRN) that is suitable for use in cognitive radio applications.

The ITRN is an end-to-end solution that can quickly find interferers and act upon them in a defensive manner such as filter, move the channel, move to different band, etc. While the ITRN is capable of finding interferers in both the spectral dimension, we present a framework that allows for future expandability into more measurement domains.

To break to sensing time tradeoff with spectral and angular resolution, we employ the use of compressed sensing (CS). By making a few assumptions on the local EM environment's current state, we are able to perform spatial and spectral scans that are a factor of 10 times faster than the current state of the art. Information on the spectral locations of the interferers, along with a current QoS estimate is then sent to a machine learning based decision engine (MLBDE) where reinforcement learning is used to determine the optimal channel selection.

For the ITRN's sensor, we use a custom 8 antenna RF-ASIC fabricated in TSMC 65nm CMOS called the Direct Space to Information Converter (DSIC). The output of the DSIC is sent to an Ettus X310 radio. A custom UHD interface was constructed in the field programmable gate array (FPGA) to speed the streaming data rate by using a variable data packet size. Custom UHD circuitry was also created to synchronize the DSIC with the clock on the X310.

In GNU Radio, we perform the baseband DSP and Orthogonal Matching Pursuit (OMP) which is used to recover the spectral locations of the interferers. Lastly, the output of OMP along with a QoS estimation is sent to the MLBDE which calculates the new optimal channel selection and retunes the ITRN.

Keywords - Cognitive Radio, Compressed Sensing, Software Defined Radio, Machine Learning, Reinforcement Learning, GNU Radio.

I. BACKGROUND AND MOTIVATION

Communications often take place in congested and contested spectral environments where conditions readily exist that impair network connectivity. Whether the impairment is due to ordinary congestion, geographical obstructions or malicious jamming, understanding the cause of the impairment and developing systems that can react to the environment, and thereby mitigate the interference, is increasingly becoming an important topic for tactical communication systems. The next generation of communications networks will need to be *EM environment aware* to effectively operate in both friendly and hostile congested RF environments [1].

These adverse effects on communications can be further characterized by their external characteristics, for example, placement in the RF frequency spectrum, angular spectrum (direction of arrival or DoA) and time can be measured to help better characterize and take action to mitigate these harmful effects or signals. This can be seen in *Figure 1* where a *multi-dimensional* resource cube is used to better understand a signal of interest's (SOI) effect on a communications node.

While *Figure 1* shows an EM state space of 3 dimensions, in reality there are many more possible dimensions that can be used to characterize the EM environment. Signal bandwidth (BW), terrain, fading and environmental noise can all be considered dimensions of an X dimensional resource cube, where X is the total number of measurement dimensions.

Additionally, the optimal actions associated with countering a particular EM disturbance can also be considered a Y dimensional state space where Y is the total possible transceiver actions (e.g., move transceiver to a different channel, change modulation type, or change BW). Sensing all X dimensions and finding the optimal transceiver action out of Y possible actions *cannot be completed in an acceptable amount of time using pre-calculated decisions or with traditional sensing systems* [1]. To minimize computation complexity and conserve energy in man-portable hardware, the system needs to learn and adapt to the numerous types of potential perturbation in the EM environment that the system may encounter. Such a system can be realized by leveraging machine learning (ML), compressed sensing (CS) and the advancements made in cognitive radio systems [2].

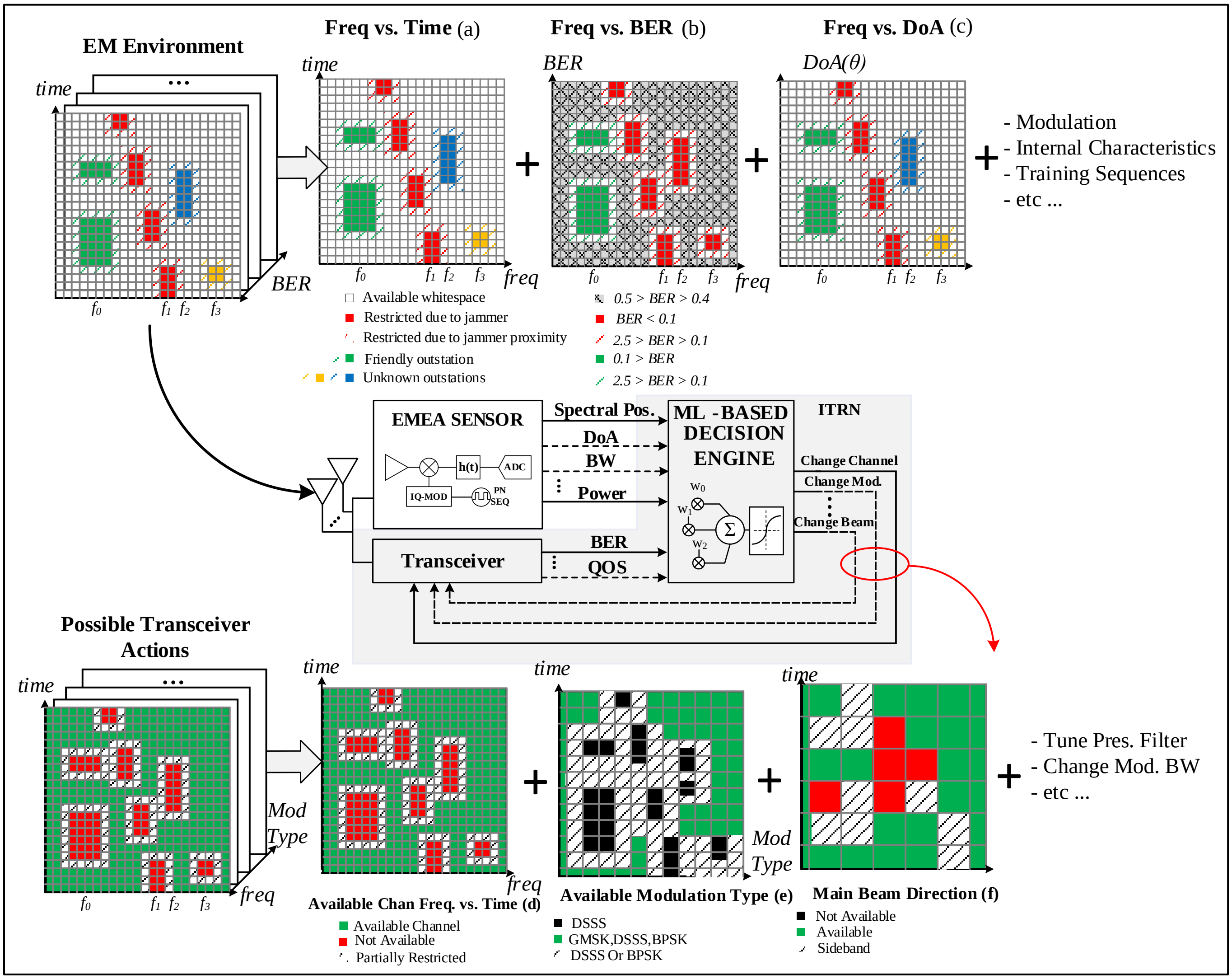


Figure 1. Illustration of an N-dimensional "resource cube" showing occupied resources in the EM environment.

In summary, this paper introduces the concept of an Intelligent Transceiver Radio Node (ITRN) that contains two submodules in addition to the transceiver system; the EM Environment Aware (EMEA) sensor and the Machine Learning Based Decision Engine (MLBDE). These components work in conjunction with each other to enable a fully-cognitive radio transceiver system capable of operating in hostile radio frequency (RF) environments.

II. Related Work and our Contributions

A. Current State of the Art

The purpose of the EMEA sensor is to provide an assessment of the state of the EM environment (e.g., locate interferers and find available whitespace in some domain).

Traditional multi-domain EMEA sensors either consume too much energy or are not able to react quickly enough to capture fast reacting jammers. Typical commercially available frequency hopping spread spectrum (FHSS) radios have a pulse repetition rate of 2-10ms and a pulse time of 1-2ms. Measurement accuracy and node awareness requires a sensor to scan over a wide bandwidth and use as many measurement domains as possible in order to fully quantify the jammer's effect on the system's quality of service (QoS). For example, if N spectral bins, N spatial bins and N temporal bins require scanning, the total number of possible signal locations in the EM environment state space is proportional to N^3, assuming DFT-like sensing matrices are used in each domain. In general, the number of measurements required will grow as a product of the measurement dimensions if traditional sensing techniques are used.

Spectral occupancy of adversarial interference, obtained from an EM aware receiver, will allow the sensor transceiver to find new spectrum allocation for maintaining the communications link.

A sample of current wideband spectrum sensing topologies is shown in *Figure 2.*

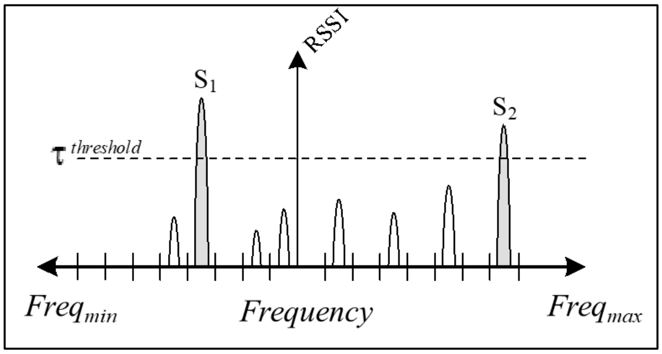


Figure 2. Illustration of sparsity in the frequency domain where K is the number of signals in the environment and N is the number of possible spectral locations. K<<N

To satisfy the scalability, speed and energy consumption requirements during sensing, energy-efficient wideband interferer detection is a key component of an EM aware receiver. Current state-of-the-art spectrum scanners rely on traditional spectral analysis that includes an intrinsic trade-off between span, resolution bandwidth and scan time. In a single branch sweeping scanner, as illustrated in *Figure 3(a)*, each bin is scanned sequentially by sweeping the LO driving the I/Q downconverter. Covering a span greater than 10 GHz with a 20 MHz RBW requires scan times on the order of 2200 us, which results in large energy consumption and an inability to track agile targets.

Parallelism, illustrated in *Figure 3(b)*, can overcome the scan-time limitations, but the energy requirements remain constant for a single-branch or a multi-branch realization. Additionally, circuit and system complexity does not scale well from a size, weight and power (SWAP) and system designer's standpoint, (i.e., for a 1GHz span and 20MHz RBW), a 50-branch realization would have a 4.4 us sensing time but an impractical hardware complexity. On the other hand, a Nyquist-rate FFT solution, shown in *Figure 3(c),* would simplify the design architecture but require a prohibitively high sampling rate after down-conversion.

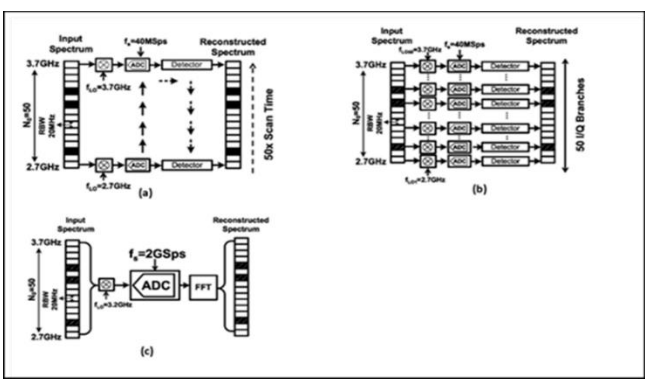


Figure 3. A survey of current spectrum sensing methodologies.

III. ITRN SYSTEM OVERVIEW

Figure 1 illustrated a 3D resource "cube" depicting the directions of incident signals including the interferers in both the angle and frequency domains for multiple time snapshots. While there are many possible locations that signals can be in, even in a crowded RF environment, only a few possible angular locations are occupied at any one given time. This RF environmental characteristic is called "sparsity" and can be seen in *Figure 3 (a), (b) and (c).*

We can exploit the sparsity of the frequency spectrum to yield circuit architectures that are faster and an order of magnitude more efficient than the current state of the art . This increase in speed and efficiency comes from the ability to use CS to sense signals with fewer random measurements than are required by a Nyquist-rate based systems [3]. For the signal vector

$$\boldsymbol{x} \in C^N$$

where

$$\boldsymbol{x} = \boldsymbol{\Psi}\, \boldsymbol{X}$$

and $\boldsymbol{\Psi}$ **is** the $N \times N$ dictionary matrix and $\boldsymbol{X}$ is an $\boldsymbol{N \times 1}$ vector with $K \ll N$ non-zero entries, with K the number of signals, CS states that $\boldsymbol{X}$ can be recovered using $m = K\ \ C_0 \log\left(\frac{N}{K}\right)$ linear projections on to a $m \times N$ sensing matrix $\boldsymbol{\Phi}$ that is incoherent with $\boldsymbol{\Psi}$[4].The system equation can be written as:

$$\boldsymbol{y} \ = \ \boldsymbol{\Phi\Psi X}$$

In the case of spectrum sensing, the $\boldsymbol{x}$ vector consists of time samples with a DFT like dictionary matrix $\boldsymbol{\Psi}$**.** Recovery of $\boldsymbol{X}$ can be performed by a variety of convex optimization algorithms. Orthogonal Matching Pursuit (OMP) is used due to its simplicity and best tradeoff in accuracy and efficiency for highly sparse problems [4]. The concept of CS based spectrum sensing can be futher seen graphically in *Figure* .

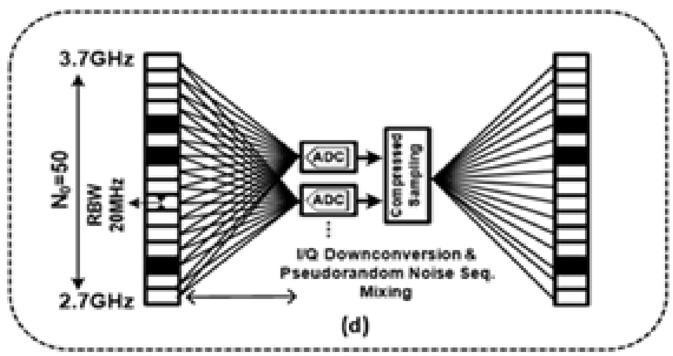


Figure 4. Illustration of a CS based spectrum sensing system.

IV. EMEA SENSOR

A. *The EMEA Sensor*

The EMEA sensor used in the ITRN is capable of performing CS based spectrum sensing and enables it to sense the wideband spectrum in fewer scans than the traditional swept LO or FFT methods in addition to consuming less power and energy. Several CS based architectures such as the MWC [5], QAIC [6], DRF2IC [7], DSIC [8] and DSS [9] have demonstrated the advantages of using CS for sensing the EM environment at the hardware level.

The entire ITRN can be seen in detail in *Figures 5*Figure *(a) and (b)* where interferers are incident upon the ITRNs antenna. The EMEA sensor quickly detects their spectral locations using a CS driven sensor architecture. The spectral locations are then sent to the MLBDE along with a measurement of the QoS (e.g., BER) of all channel locations. The MLBDE informs the ITRN of which new channel location is optimal.

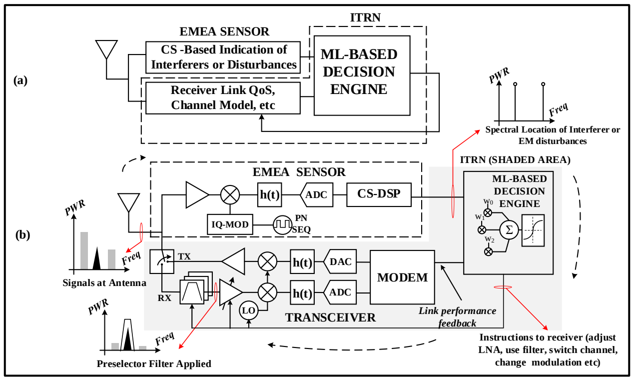
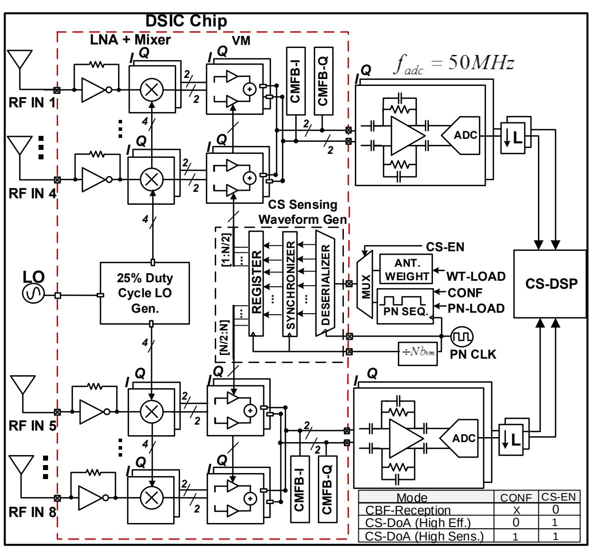


Figure 5. (a) High-level diagram of the ITRN (b) Detailed circuit level description

For this effort, the EMEA sensor used is the direct space to information converter (DSIC). The DSIC is capable of operating in many modes of operation (e.g., angular sensing, spectrum sensing, etc.). For this application, it is placed into spectrum sensing mode with a tunable frequency range of 500MHz to 3GHz. The DSIC is a direct downconversion architecture and contains 8 antenna paths split into two banks of 4. All antenna paths are complete with independent LNAs, mixers and vector modulators (VMs). The return loss (S11) at the antenna inputs is nominally better than -10dB from 1GHz to 3GHz. Conversion gain of each single receiver path with the VM adjusted to maximum amplitude is 32dB across an IF BW of 25MHz, NF, P1dB, and in-band IIP3 of each path at 1.5GHz are 6.4dB, 11.3dBm, and 3.3dBm respectively. A detailed circuit diagram of the DSIC is shown in *Figur*.



Mode	CONF	CS-EN
CBF-Reception	X	0
CS-DoA (High Eff.)	0	1
CS-DoA (High Sens.)	1	1

Figure 6. A circuit diagram of the DSIC which is used as the ITRN's EMEA sensor.

The output of the DSIC (***y***) is first sent to a digital branch expansion module. The branch expansion module digitally downconverts *m* channels where each channel corresponds to a CS measurement. A detailed description of the branch expansion process can be seen in [7]. After branch expansion, the CS meaurements are sent to the OMP module where lastly, the spectral "supports" or SOIs are recovered. More details on the concept behind OMP can be seen in [4].

Figure and *Figure* show the performance in terms of probability of detection and false alarm (P_d and P_{fa}) can be seen for the DSIC which a varying number of signals K in the environment as well as signal position vs. incident signal power in dBm. The EMEA sensor is capable of detecting K=3 signals with as little as m=19 CS measurements with a P_d >90%.

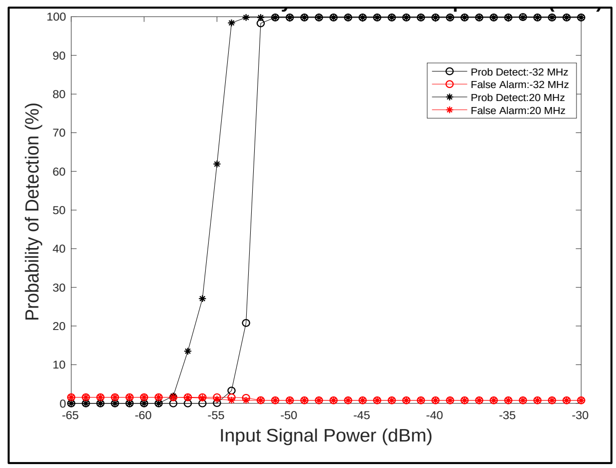


Figure 7. Input signal power vs. probability of detection (Pd) and false alarm (Pfa) for varying interferer position and K= 1 interferer.

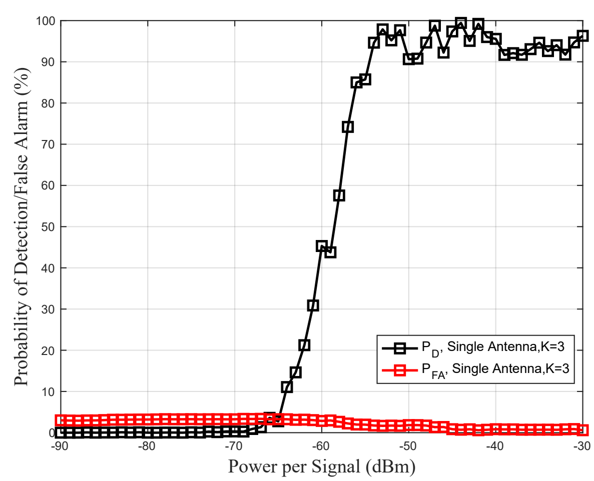


Figure 8. Input signal power (dBm) vs. Pd and Pfa for K=3 interferers.

V. MACHINE LEARNING BASED DECISION ENGINE (MLBDE)

The goal of the ITRN system's MLBDE module is to compute in real-time an optimal recommended frequency bin that is both robust and high-performing. The MLBDE-recommended frequency bin is sent to the GNU Radio for dynamic tuning of the SDR configuration so that the SDR waveform will operate on a frequency bin that is best in terms of minimizing outages due to signal interference (i.e. *robust*) and minimizing the average channel bit error rate (i.e. *high-performing*). To compute an optimal recommended frequency bin, the MLBDE module processes spectrum sensing data streamed to it real-time from the EMEA CS module over a UDP socket interface.

A. ML Channel Sensing Inputs

The input sensing data received from the EMEA CS module consists of: (1) a list of IDs of frequency bins that are interfered (e.g., due to spectrum congestion or up to 10 such interfered bins) and (2) an array of bit error rate (BER) floating point values (up to 128 such values depending on the number of frequency bins).

While the MLBDE module considers for each scan interval / policy action update the entire list of interfered bins as context in its decision logic, the MLBDE module's ML decision logic is aware only of the BER value for the frequency bin it has recommended (and only *after* the bin has been selected to assure performance evaluation fairness). This BER value is needed to quantify the reward of its recommended frequency bin (and to update the cumulative reward and average reward scores).

B. Multi-Armed Bandit (MAB) ML Problem Formulation

The contextual multi-armed bandit (MAB) problem has been applied as a generalized abstraction for many practical applications [10]. The ITRN dynamic radio adaptation challenge represents another opportunity for which the contextual MAB problem formulation is applicable and to which machine learning (ML) techniques can be applied. In the MLBDE solution, the reward obtained by selecting a specific arm/action k (i.e., the action of selecting frequency bin $A_t = k \in \{1,2,\ldots,K\}$) at each step t is the complement of BER (i.e., $R_t(A_t = k) = 1 - q_t(k)$ where $q_t(k)$ is the BER for frequency bin k over the interval associated with time step t). The MLBDE performance metric evaluated over N steps is the average step-by-step reward ($\bar{R}_N$):

$$\bar{R}_N = \frac{1}{N}\sum_{t=1}^{N} R_t = \frac{1}{N}\sum_{t=1}^{N}\left(1 - q_t(A_t)\right) \tag{1}$$

As one of the data structures applied in its MAB decision logic to select a frequency bin (per Section **Error! Reference source not found.**.C, next), the MLBDE maintains the average reward obtained for the occurrences of selecting frequency bin k over the course of N steps $\{1,2,\ldots,N\}$ ($\bar{R}_N(k)$) for each frequency bin $k \in \{1,2,\ldots,K\}$. Using the indicator function notation of "**1**" 〖_(A_t = k)〗^ $= 1$ if $A_t = k$ and 0 otherwise, the average reward obtained when selecting frequency bin k through N steps is the sum of rewards yielded by selecting frequency bin k divided number by the number of times frequency bin k was selected over the N steps $\{1,2,\ldots,N\}$:

$$\bar{R}_N(k) = \frac{\sum_{t=1}^{N} R_t \cdot \mathbf{1}_{A_t=k}}{\sum_{t=1}^{N} \mathbf{1}_{A_t=k}} \tag{2}$$

Table 1 summarizes the MAB policies/heuristics implemented as part of the MLBDE policy suite to process the channel information received from the EMEA-CS module and output a recommended frequency bin. While all four versions of "hybrid-greedy" heuristics listed in *Table 1* provide effective means to facilitate the tradeoff between exploration and exploitation, the Epoch-Greedy procedure [10] intuitively is most practical for the challenge at hand by providing configurable control over the schedule by which the performance of alternative frequency bins are explored followed by a window in which the best performing frequency bin is exploited. Random policy procedures are implemented as part of the MLBDE policy suite primarily for comparison purposes where the pure random policy serves as a baseline for performance evaluation against which other MAB policies/heuristics are compared.

Table 1. MAB Policies/Heuristics Implemented

Policy / Heuristic	Description of Policy/Heuristic
Random	Periodically select a random frequency irrespective of the interfered frequency set or its past selections
Sticky Non-Interfered	A new frequency is not explored unless the current frequency is under interference
Random Non-Interfered	Periodically select a random frequency as long as the frequency is not under interference
ε-Greedy	Perform random exploration with probability ε (exploration) but use best frequency o/w (exploitation)
ε-First	Perform pure exploration for first εN trials and then pure greedy exploitation for remaining $(1 - \varepsilon)N$ trials
ε-Decreasing	Similar to ε-Greedy, but uses a decreasing ε value as the experiment progresses
Epoch-Greedy	Experiment proceeds as a sequence of epochs where, in each epoch, exploration of new frequency bin(s) is pursued first followed by exploitation of the best frequency bin for the remainder of the epoch

C. ML Decision Logic for Greedy Heuristics

While the reward metric Eq. (1) is used to quantify performance of the MLBDE module, the ML decision logic for its greedy heuristics must decide in each *exploitation* phase which frequency bin $k \in \{1,2,\ldots,K\}$ should be selected for action A_{N+1} (and subsequent exploitation steps). For this purpose, the ML decision logic considers the average reward afforded by each frequency bin per Eq. (2).

Furthermore, the ML decision logic also considers the set of interfered frequencies (S_t) inputted at each time step as *side information* which MLBDE leverages as a form of context (i.e., if frequency bin $x \in S_t$ then the expected reward in choosing x is low and bin x should not be selected). Therefore, aside from the pure random policy, the MLBDE-recommended frequency bin for the action at step t (either for exploration or exploitation), excludes candidate frequency bins that are interfered (i.e., in the set S_t).

Two variations of the decision logic for greedy exploitation have been implemented. First, (3a) applies a basic decision logic metric that combines the frequency bin performance per (2) with awareness of currently interfered bins (S_{N+1}) as context by which to prune the set of candidate bins.

$$A_{N+1} = \max_{\substack{k\in\{1,2,\ldots,K\},\\ \{k\}\cap S_{N+1}=\emptyset}} \bar{R}_N(k) \tag{3a}$$

Next, Eq. (3b) represents a compound decision logic metric that additionally considers the history of signal interference where $s_N(k)$ is a cost term that discourages selection of (otherwise high-performing) bins that are unfortunately frequently interfered. Here, the term $s_N(k)$ is the fraction of steps (out of the N steps $\{1,2,\ldots,N\}$) for which frequency bin k was interfered. The intuition for applying the compound decision logic metric of (3b) is that it will promote selection of more robust (i.e., less likely to be interfered) frequency bins for exploitation.

$$A_{N+1} = \max_{\substack{k\in\{1,2,\ldots,K\},\\ \{k\}\cap S_{N+1}=\emptyset}} \bar{R}_N(k) - s_N(k) \tag{3b}$$

D. Proof-of-Concept Validation Results

The MLBDE software was validated in standalone mode using channel sensor input data collected offline and saved to file. At experiment time, the sensor data was read from file and sent at "high speed" (e.g., ~662 Hz) by a unit-test driver module to the MLBDE component via a UDP socket API. *Table 2* summarizes the preliminary proof-of-concept MLBDE validation results. Epoch-Greedy was the ML heuristic enabled in the experiments behind these results.

Table 2. MLBDE Proof-of-Concept Validation Tests

Test Purpose	Result / Key Finding
Compare Random versus Greedy	ML with greedy heuristics reduces avg. BER of selected frequency bin by factors of 7.76 to 26.9
Process short scan interval updates	For 101 freq. bins and 10 interfering signals, ML processed updates every ~1509 µs in real-time
Validate use of interference info	ML leveraged interfering signal side info to reduce avg. BER by factor of 2 (versus w/ none)
Verify shift to robust bins by (3b)	Compound metric per (3b) shifts the selected bin preference to less interfered bins by up to 74%

VI. Implementation of the ITRN

Construction of the ITRN was assisted by the use of the GNU Radio framework and UHD and this is shown in *Figure* and *Figure*. *Figure* shows the BER calculation circuit that establishes a link's QoS with an outstation, and *Figure* shows all major signal processing blocks required for the ITRN to operate. An m= 19-channel baseband channelizer is used to collect the CS measurements before being sent to the OMP engine to extract the K signals in the EM environment. The number of signals to detect K, as well as OMP residue and threshold, are all configuration inside the OMP engine running in GNU Radio. Once the OMP engine finds the K signals, it sends them as a vector to the MLBDE along with the BER of all channels the ITRN can possibly use.

It is necessary to synchronize the start and end of the CS measurement PN sequence with the digital channelization circuit built in GNU Radio. To do this, we use a "sync-pulse" that is sent from the EMEA sensor. The sync-pulse propagates through a pulse extender board and then to the Ettus X300 front panel GPIO connector. UHD typically uses 32 bit complex sample (16 bit I and Q) where bits 14 and 15 are zeros. By default, each channel sends 32 bits of data to GNU Radio for each sample. Because of the low dynamic range and high throughput requirements, the data vector was manipulated to include 14 bits of IQ data per channel and the sync signal in a single 32 bit vector, effectively doubling the throughput.

The simplest way to modify the existing FPGA code to accomplish this was to modify the DDCs to share IQ data between each other and have the GNU Radio application receive data from a single DDC. This can be seen in *Figure 9*.

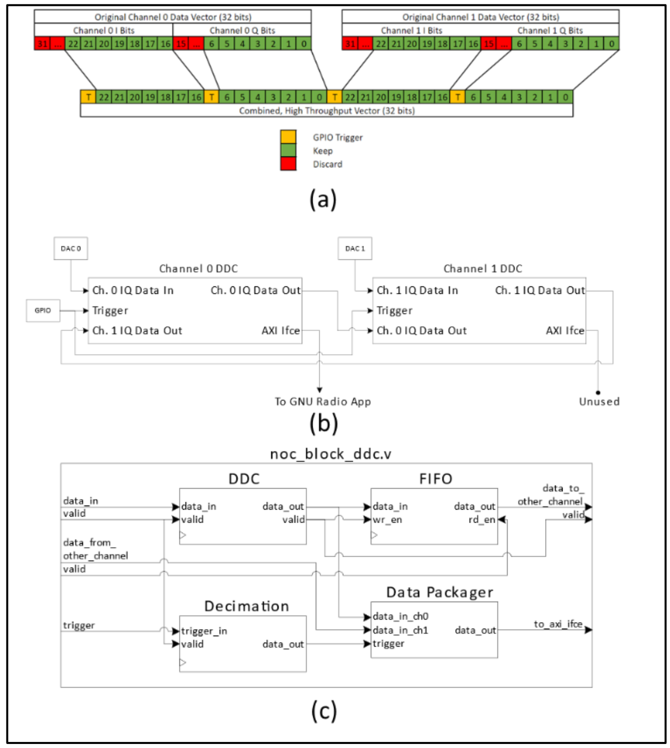


Figure 9. Implementation of the new FPGA data format and sync signal incorporation.

In this configuration, no changes had to be made to the existing AXI interfaces, which would have been more time-consuming. Where the DDCs are instantiated in the FPGA code, signals were created to send the down-converted IQ output of each DDC and its valid signal to a new input of the other DDC. It was discovered that the two DDCs do not necessarily output valid data on the same clock cycles. To correct for this, inside of one DDC, the valid data from the other DDC is written to a FIFO and then read out when the first DDCs data is valid. This ensures all data sent to GNU Radio will be valid, and without this buffer, one channel's data will appear discontinuous. Before the DDC sends data to GNU Radio, it packages its own down-converted IQ, the down-converted IQ from the other channel, and the sync signal into a 32 bit word.

The sync signal requires decimation to match the decimation rate of the DDC. The decimation rate of the sync signal is calculated based on the half-band filter rate and the the CIC decimation filter rate of the DDC. To preserve timing of the sync relative to the IQ data, it is buffered using a FIFO, which is read from when the DDC outputs valid data.

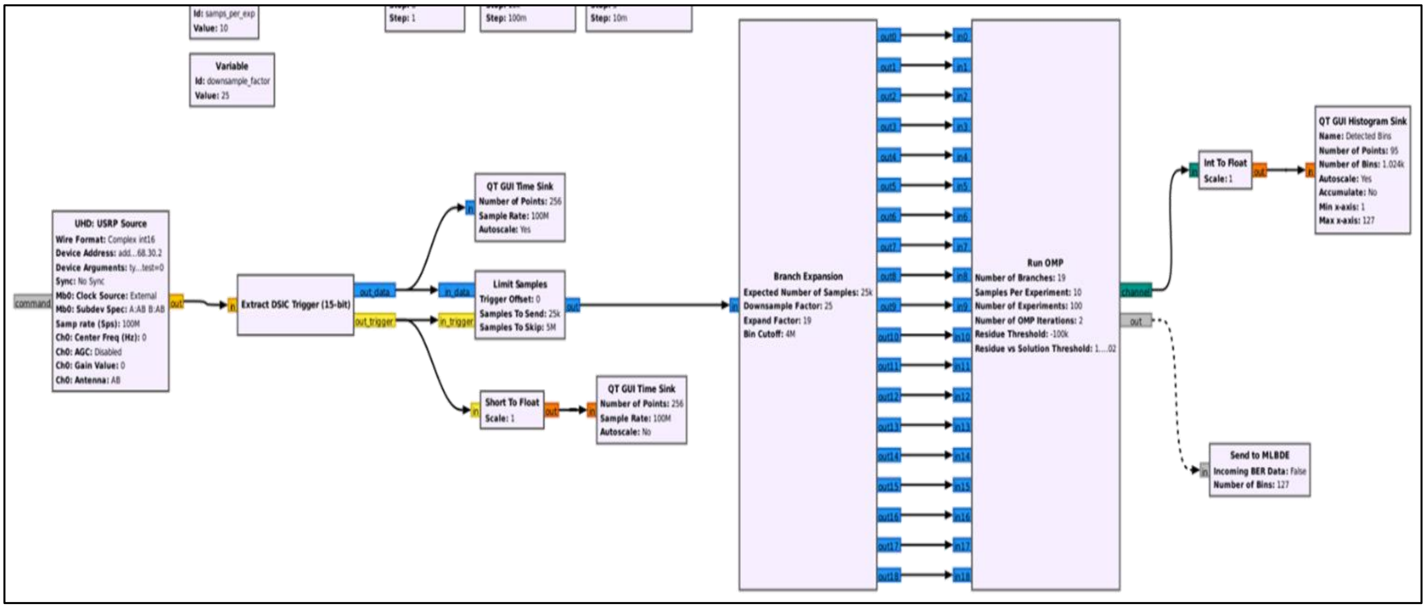


Figure10. The entire ITRN system using the GNU Radio framework.

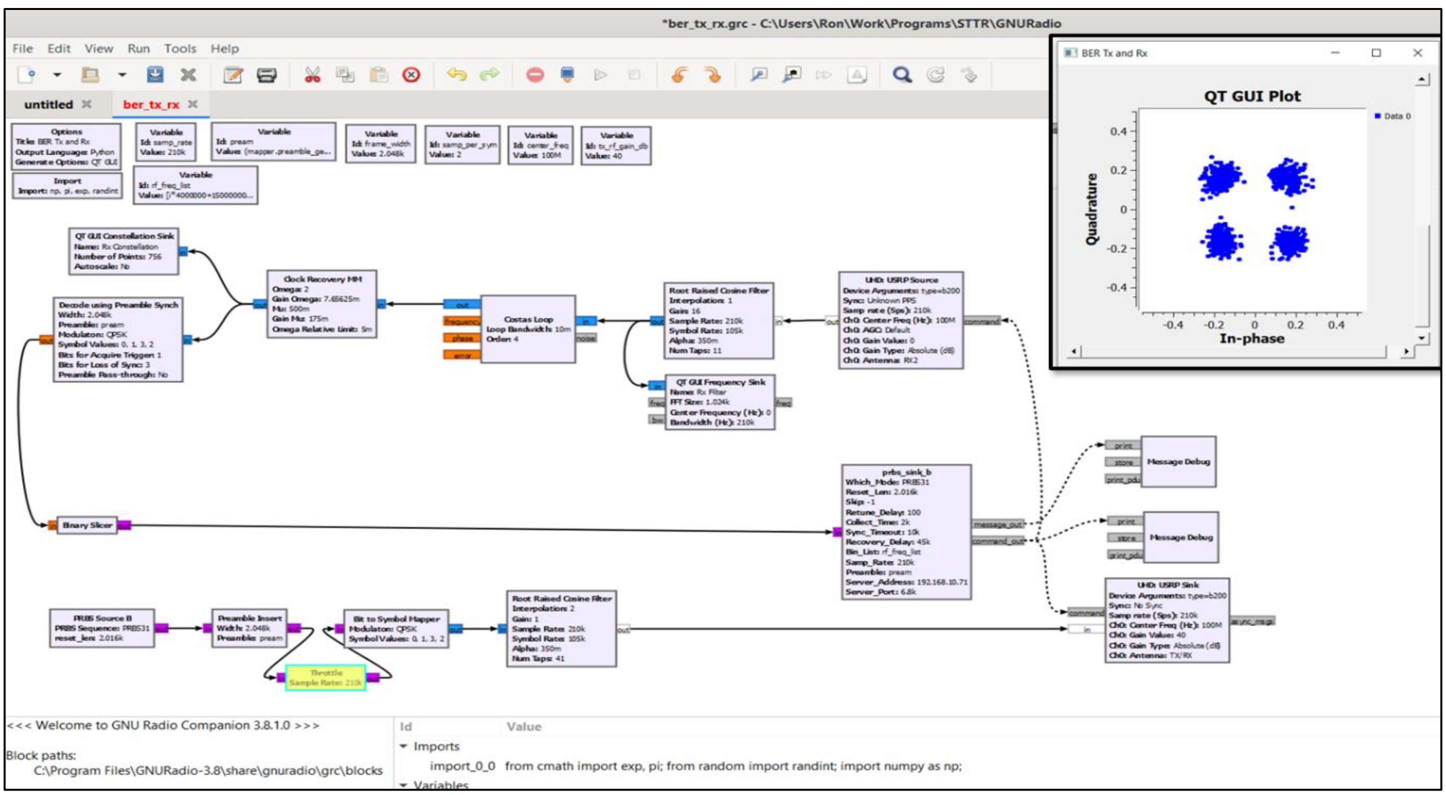


Figure 11. The BER calculation circuit constructed using GNU Radio

Further, the delay of the sync signal through the FPGA is kept equal to the IQ data delay by embedding the sync in the MSB of the IQ data. This approach is valid assuming that the ADCs will not be saturated by the received signal. Special care must be taken to extract and reinsert the sync any time a mathematical operation is being done on the IQ data (e.g., front end correction, down-conversion).

VII. PERFORMANCE AND COMPARISON

Performance of the ITRN is characterized based on the independent performance tests of the EMEA sensor and MLBDE as seen above, as well as the construction and test of a prototype testbed suitable for data collection and demonstration. The ITRN testbed system diagram can be seen in *Figure 12*. Multiple signal generators are connected to the ITRN testbed simulating a variety of wideband, narrowband and frequency hopping interferers over a 500MHz RF bandwidth. To successfully sense this environment, the EMEA sensor is programmed with a 508MHz PN clock, 1.5GHz LO and 127-bit PN sequence resulting in 4MHz channels and up to 19 CS measurements.

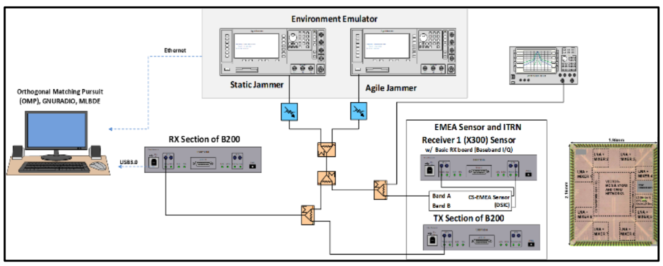


Figure 12. Circuit diagram showing the ITRN testbed with locations of critical components.

Figure 13 shows a screenshot of the system GUI. In the top left, MLBDE output (green) as well as instantaneous interferer detections from the EMEA sensor can be seen. In the top right, the QoS for all channels (measured as BER) is also seen. Note the high BER in the middle of the 508MHz band coincident with the frequency hopping interferer locations. The bottom right shows the aggregate interferer detections from the EMEA sensor over 100 scans. Lastly, the bottom left shows a running waterfall of the EMEA sensor's interferer detections. Also refer to the attached videos for more information on how the ITRN prototype testbed functions.

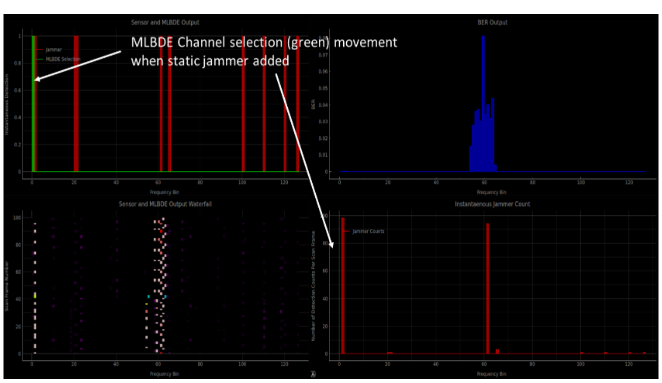


Figure 13. Testing graphical user interface (GUI) screenshot.

VIII. CONCLUSIONS

In this paper we showed the design and test of an intelligent transceiver radio node (ITRN) that is suitable for use as a cognitive radio (CR) component. It uses a Compressed Sensing (CS) driven receiver architecture that is used to sense the RF spectrum in a fraction of the time as current state-of-the-art techniques. To demonstrate the capability of the ITRN, an EM environment aware sensor (EMEA) was successfully integrated into the GNU Radio framework, the output of which indicates the spectral position of jammers or interferers.

Jammer location is sent to a machine learning based decision engine (MLBDE) which in turn takes appropriate action (retunes, switches band, etc.) by making the optimal corrective decision based on reinforcement learning. The ITRN requires far less time to find interferers in frequency domain. Where Nyquist rate spectrum sensors require N measurements, the ITRN requires only m where $m = K\ C_0$ where K<<N, N is the number of possible interferer locations and K is the number of interferers the ITRN is programmed to find. Output of the ITRN's EMEA sensor is sent to the MLBDE where reinforcement learning allows the ITRN to find the most optimal decision on where to retune.

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