Assessment of Cognitive Communications Interest Areas for NASA Needs and Benefits

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Abstract— **This effort provides a survey and assessment of various cognitive communications interest areas, including node-to-node link optimization, intelligent routing/networking, and learning algorithms, and is conducted primarily from the perspective of NASA space communications needs and benefits. Areas of consideration include optimization methods, learning algorithms, and candidate implementations/technologies. Assessments of current research efforts are provided with mention of areas for further investment. Other considerations, such as antenna technologies and cognitive radio platforms, are briefly provided as well.**

Keywords—cognitive, intelligent, machine learning, adaptive, satellite, wireless, communications.

I. Introduction

As NASA future mission plans continue to evolve, new technologies and capabilities will be introduced into the space communications architecture to accommodate the anticipated mission needs. The envisioned future architecture will include new technologies, such as optical communications, and will be more inter-networked in nature with user missions communicating over various architectural elements, including relay and surface assets. The implementation of cognitive communications systems within the architecture may offer the potential for improved automation and efficiency. These potential advantages as well as the risks and complexities are currently under study and evaluation by test platforms such as the SCaN Testbed.

Cognitive communications covers a wide set of topic areas and expands upon the cognitive radio (CR) concept. A cognitive radio senses its environment and uses adaptive and learning mechanisms to dynamically alter and optimize its communications parameters (coding, modulation, data rate, etc.) to enhance overall throughput while attempting to avoid interference with other cognitive and non-cognitive users. Cognitive communications expands beyond link-level optimization strategies to encompass a broader range of optimization areas spanning multiple layers of the Open Systems Interconnection (OSI) protocol model. These areas include intelligent networking and routing, system-level intelligence, intelligent radio platforms, and others. Efforts to enhance cognitive communications capabilities is envisioned to benefit many user applications, including satellite communications systems, as well as terrestrial wireless systems. This can result in increased data return, new science observation capabilities, improved asset and resource efficiencies, and enhanced overall user experience.

A cognitive communications system, in general, functions in a closed-loop manner, where the system (1) observes its communications environment, (2) makes a decision on a how to optimally utilize the communications medium based upon its acquired knowledge, (3) performs appropriate actions based on the decision, and (4) learns from the results of its chosen activity. This model allows a cognitive communications system to optimally perform within its environment [1].

The following sections describe cognitive communications efforts in the various areas mentioned – link-level optimization, intelligent network/routing, and learning algorithms. Each sub-section provides an overview of the approach, followed by implementations, candidate technologies, and possible areas for further investment.

II. Link-Level Optimization

At the physical and link layers of the OSI protocol model, link-level optimization mechanisms are used to enhance performance of communications conditions by altering parameters such as coding and modulation schemes. Additionally, the implementation of spectrum sensing and interference-avoidance mechanisms are used to exploit use of unused portions of the radio spectrum. These link-layer optimization methods are described in the following sub-sections.

A. *Interference Mitigation Mechanisms*

A cognitive radio exploits information observed about its environment to improve spectrum utilization. This information may include knowledge concerning the activity of other nodes (cognitive and non-cognitive) that share radio spectrum with the cognitive device. This allows the sharing of radio spectrum with concurrent users in a manner that strives to minimize or eliminate interference. Based on the information sensed about its environment, cognitive radio systems may use the underlay, overlay or interweave approach to share the spectrum with other cognitive and non-cognitive users [1].

1) Underlay Paradigm: The underlay paradigm requires transmissions from the cognitive device to occur only if the interference level observed by the primary (non-cognitive) users is below a specified threshold. Meeting this minimum interference requirement may be achieved by focusing transmissions away from primary users (via directional antennas), or by using spreading techniques that reduce the signal level to below the required interference threshold. Spreading techniques may include spread-spectrum (e.g., Code Division Multiple Access) or ultra wideband (UWB) transmission, for example. The signal may then be de-spread at the receiving node.

2) Interweave Paradigm: In the interweave mode of operation, the cognitive radio periodically monitors the radio channel to find unused portions (or "white spaces") of the radio spectrum and makes a decision on whether or not to exploit that unused spectrum for its own communications needs. If exploited, the cognitive system may transmit without power constraints since the portion of the spectrum is currently unused and will likely not cause any interference to primary (i.e., licensed) users. The interweave mode of operation was conceived after the FCC conducted studies and discovered that significant portions of the radio spectrum were not used most of the time. This allows cognitive users to sense and utilize these spectrum holes. Fig. 1 provides an illustration of the Underlay and Interweave paradigms.

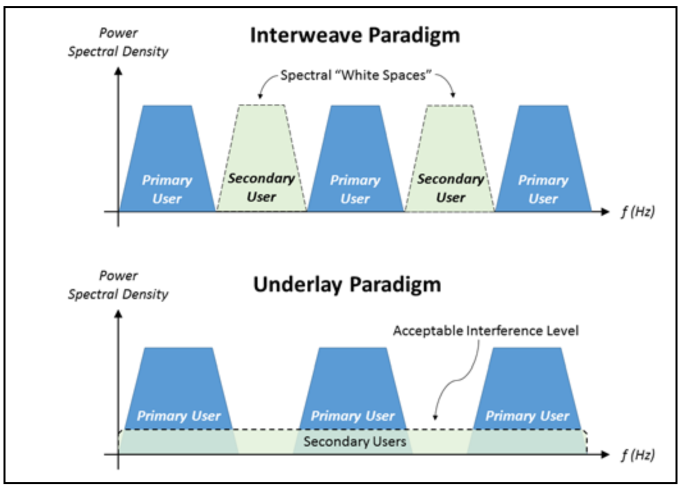

Fig. 1. Overview of Interweave and Underlay Spectrum Usage

3) Overlay Paradigm: Overlay paradigm operates in a manner such that a cognitive system has knowledge of non-cognitive system's messaging and/or encoding schemes. From this knowledge, the cognitive system can assist the non-cognitive user in relaying its transmissions in instances of interference or fading, while also using the communications medium for its own purposes. The cognitive system could also potentially cancel the effect of interference by receiving the non-cognitive user's transmission and using signal processing and/or encoding techniques to retransmit the information to the receiver. The overlay paradigm is applicable to both licensed and unlicensed spectrum bands since its operation does not incur interference with other users and may even improve performance during instances of interference or fading [1] [2].

In any of the aforementioned interference mitigation schemes, a cognitive radio must sense its environment to determine its most appropriate course of action. The number of antennas and the respective configuration depends on the interference scheme.

In the case of the Underlay paradigm, a single wideband antenna can be used with reconfigurable notch frequencies. The reconfigurable notch frequency is employed to prevent interference with primary users that do not allow any sharing spectrum.

An interweave system may use either one or two antennas, where in the case of one antenna, the system must switch between spectrum sensing and primary operation. Typically, two antennas are preferred for this paradigm. An example of an antenna system for interweave operation consists of a wideband sensing antenna consisting of a printed monopole, and a reconfigurable antenna that can adjust its operating frequency by using silicon switches. The wideband antenna produces an omnidirectional radiation pattern over frequencies ranging from 3 GHz to 10 GHz. Additional efforts are also investigating radiation patterns at Ka-band. Other configurations for the various interference schemes are further described in [1].

B. Variable and Adaptive Coding and Modulation

As the name suggests, Variable Coding and Modulation (VCM) and Adaptive Coding and Modulation (ACM) are mechanisms that allow for the adaption of channel coding, modulation scheme, and other signal parameters based on the conditions of the communications channel. These link conditions may be a result of interference from other users, the path loss from transmitter to receiver due to weather-related fading, antenna pointer errors, or other factors. By using these adaptive mechanisms, link designers do not necessarily have to rely on a worst-case link margin to overcome those periodic link impairments; rather by using VCM/ACM, communications links may use link margin which was previously reserved to ensure link availability in high-fade conditions.

VCM techniques are effective when link dynamics can be accurately predicted, such as instances of link fading due to occultation from obstructions that appear on a periodic basis. ACM extends VCM by allowing feedback from receiver to transmitter for dynamic alteration of communication parameters based on current propagation conditions.

Feedback for ACM systems may be achieved in various ways, one of which assumes link reciprocity (i.e., the channel conditions from the transmitter to the receiver is approximately the same as in the reverse direction), and therefore the transmission parameters may be adjusted based on characteristics of the forward link; or alternatively, the channel knowledge can also be directly measured at the receiver, and provided back to the transmitter via the return link.

The Digital Video Broadcasting Satellite – Second Generation (DVB-S2) standard provides an error correction capability based on low-density parity check codes (LDPC) that approaches the Shannon limit. The standard accommodates a range of modulation formats from quadrature phase-shift keying (QPSK) to 32 amplitude and phase-shift keying (APSK). DVB-S2 supports both VCM and ACM in addition to the constant coding and modulation (CCM) profile provided by its predecessor, DVB-S [3].

As described in [4], experiments of DVB-S2 over satellite using VCM and ACM have been demonstrated and shown improvements in system throughput. The experiment consisted of a direct-to-Earth link from the SCaN Testbed on the International Space Station (ISS). Software Defined Radios (SDRs) loaded with the DVB-S2 waveforms transmitted data to the ground system, and a decision algorithm selected the most appropriate modulation and encoding (MODCOD) scheme based on the channel conditions. The selected MODCOD information was relayed back to the SDR via a low-rate binary phase-shift keying (BPSK) feedback link. Results of the experiment demonstrated a more than 4 dB improvement in user information throughput over standard CCM waveforms.

In addition to satellite applications, ACM is also used in wireless communications, including the IEEE 802.11 (Wi-Fi), IEEE 802.16 (WiMAX) standards and others. The use of ACM allows wireless technologies to optimize throughput, yielding higher throughput over long distances. The selection of modulation/coding is made according to a channel quality feedback indictor is used, where downlink channel quality can be assessed by the mobile and then forwarded to the base station, and/or the base station can estimate the quality of the forward channel based on signals received by mobile users [5].

C. Adaptive Pre-Distortion

The transmission of wireless signals through a non-linear channel results in signal distortion at the receiver that can make symbol recovery difficult. Therefore, implementation of a compensating mechanism to offset the non-linear nature of communications channel is an important consideration. One method of linearization is accomplished through a method referred to as pre-distortion, where a compensation system is used to pre-distort the signal prior to transmission over a non-linear channel, which results in an overall linearization of the system response from input to output. A cognitive receiver system can observe and relay channel information back to the transmitter to continually refine the compensation algorithm for improved linearity of the end-to-end system [6].

III. Intelligent Networking and Routing

Cognitive communications systems may also exploit higher layers of the OSI protocol model to allow an intelligent networking and routing paradigm. Various mechanisms that lead to an intelligent networking capability are currently under study and are briefly described in this section.

The use of conventional Internet protocols used by terrestrial applications are not ideally suited for the intermittent and long-latency links that are characteristic of interplanetary network distances [7]. The DTN concept, however, uses store-and-forward techniques to compensate for intermittent and long-latency link connectivity, and makes use of the Bundle Protocol (BP) which functions as an overlay between the network applications and the underlying communications protocols of the network nodes. BP has been demonstrated in a number of ground-based and space-based experiments, including various experiments on the International Space Station (ISS). The use of DTN has potential application in military operations where transmission and reception of vital information can be achieved despite the intermittency and dynamic nature of the communications links. The potential benefits of DTN in military applications is still under evaluation [8] [9].

In recent years, researchers have conducted on-orbit networking experiments on the ISS, such as experimenting with IP over CCSDS protocols as well as DTN and security mechanisms. Expanding this effort to encompass the broader cognitive communications envelope, researchers at GRC have initiated an effort to develop and mature advanced networking technologies to better support future space communications user needs. This effort is referred to as NASA InTelligent ROuting (NITRO). NITRO technology will provide the networking foundation to support the advances made by others in the cognitive communications interest areas (e.g., link optimization and user-initiated services). NITRO is intended to operate autonomously and selects appropriate routing based on overall system conditions. As always, security is an important consideration, and efforts are underway to advance security techniques at multiple layers to support the user mission community as much as possible [10].

The Consultative Committee for Space Data Standards (CCSDS) DTN Working Group within the Space Internetworking Services (SIS) area provides specifications for DTN, including the BP standard, the Licklider Transmission Protocol (LTP) standard, and associated protocols for network management and security. The working group leverages efforts completed by the Internet Research Task Force's DTN Research Group, which concluded its efforts in 2016 [11] [12].

IV. Machine Learning Algorithms

The benefits afforded by cognitive systems are rooted in its ability to function in an intelligent manner. A cognitive system perceives its environment, classifies its observations into categorizes (i.e., establish a base of knowledge), performs reasoning, and make use of acquired knowledge to enact appropriate decisions based on its operational objectives. Many learning algorithms are applicable to cognitive systems (such as hidden Markov models, genetic algorithms, and neural networks), where the overall intent is the use of an objective function to optimize parameters of its application. ML algorithms can be generally categorized as unsupervised, supervised, and reinforcement, which can be applied based on the operational environment [13] [14] [15].

For situations where a cognitive system is placed in an unfamiliar situation with a lack of any prior knowledge of its environment, autonomous unsupervised algorithms may be most appropriate. Unsupervised algorithms infer knowledge of its environment from acquired observational data that has not been labeled or classified. Additionally, there are no feedback mechanisms within this learning category, and the response of such algorithms cannot easily be evaluated due to lack of an available baseline for comparison.

In situations where the cognitive system has advanced knowledge of its environment, supervised learning techniques may be most appropriate. In this case, the system has labeled training data available, which it uses to produce an inferred function that maps input data to a desired output value. This allows the learning algorithm to strategize an approach to responding to new inputs in a way that is reasonable based on its acquired experience.

Reinforcement learning algorithms take actions in an environment with the intent on maximizing the "reward" derived from the actions taken. Reinforcement learning can use both trial-and-error and delayed reward approaches to exploring its environment. As the name suggests, in the trial-and-error approach, the cognitive system has no prior knowledge of its environment and makes decisions in an effort to explore and learn about its environment. The delayed reward approach involves positive or negative feedback based on the selected actions, and the system works toward achievement of maximum reward while exploring its environment.

Deep Learning is a classification of Machine Learning that uses multiple layers of processing units for feature extraction and transformation, and the output of one layer serves as the input to another layer. Deep Belief Network (DBN) is one such application of Deep Learning and has been used for Automated Modulation Classification (AMC) by pattern recognition of the Spectral Correlation Function (SCF) data. As described in [16], the DBN-based identification scheme is able classify the modulation techniques by learning the SCF patterns. Even in the presence of noise, the identification mechanism is able to achieve classification with a high degree of accuracy (i.e., approximately 90% with a signal-to-noise ratio of at least -2 dB).

V. Other Areas of consideration

The cognitive communications research area has expanded to encompass a large number of individual topic areas. This survey provided an overview that focused mostly on link optimization, advanced networking concepts, and the fundamentals of machine learning as applied to cognitive systems. Additional efforts are underway that include areas such as system-wide intelligence and intelligent radio platforms as well.

System-wide intelligence concepts allow users to 1) dynamically and autonomously schedule real-time network services by using cognitive engines and other intelligent mechanisms, 2) determine optimal link configurations based on a range of observed metrics such as past performance and available resources, and 3) achieve system-wide cognition through the use of an array of individual cognitive agents.

Intelligent radio platforms include both ground and space-based systems such as self-configuring hardware for performance optimization, smart and/or reconfigurable antenna systems, and processor architectures for cognitive processing.

VI. Conclusions

A survey and assessment of various cognitive communications interest areas was presented, including node-to-node link optimization, intelligent routing/networking, and learning algorithms, The survey provided an overview of the methodologies, algorithms, relevant technologies, and assessments of potential areas of further investment, where applicable.

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