INVITED PAPER *Special Section on Dynamic Spectrum Sharing for Future Wireless Systems*

A Survey on Spectrum Sensing and Learning Technologies for 6G

Zihang SONG[†], **Yue GAO**[†a)], ***and*** **Rahim TAFAZOLLI**[†], ***Nonmembers***

SUMMARY Cognitive radio provides a feasible solution for alleviating the lack of spectrum resources by enabling secondary users to access the unused spectrum dynamically. Spectrum sensing and learning, as the fundamental function for dynamic spectrum sharing in 5G evolution and 6G wireless systems, have been research hotspots worldwide. This paper reviews classic narrowband and wideband spectrum sensing and learning algorithms. The sub-sampling framework and recovery algorithms based on compressed sensing theory and their hardware implementation are discussed under the trend of high channel bandwidth and large capacity to be deployed in 5G evolution and 6G communication systems. This paper also investigates and summarizes the recent progress in machine learning for spectrum sensing technology.

key words: *cognitive radio, spectrum sensing, compressed sensing, machine learning*

1. Introduction

With the rapid growth of broadband wireless services, the demand for spectrum resources has increased substantially. As 5G entering the commercial stage, it becomes incredibly urgent, feeding a larger consume of spectrum bandwidth. At the 2017 IMT-2020 Summit, the promotion group has forecasted that in the sub-6 GHz frequency band, the overall demand for 5G spectrum will reach 808 MHz~1078 MHz, and the demand in high frequency (over 6 GHz) will reach 14 GHz to 19 GHz [1]–[3]. At MWCA2018, the US Federal Communications Commission (FCC) committee members stated in a speech at MWCA2018 that 6G will move towards the era of terahertz frequencies.

As a non-renewable resource, the radio spectrum frequency band used for mobile communication is already extremely limited. However, some non-technical factors, such as fixed spectrum policy limitations, slow generational refarming process of mobile communications, and high cost of spectrum acquisition, further aggravate the gap between spectrum supply and demand [4]–[6]. A great deal of research has indicated that both spatial and temporal utilization of the massive licensed spectrum resources is inefficient. FCC has pointed out that the average utilization rate of the spectrum at any time and any place does not exceed 5% [7].

Spectrum sharing, as a critical concept in cognitive radio (CR), refers to the use of electromagnetic spectrum in a designated frequency band by two or more users. Sharing users can be divided into primary users (PUs) and secondary users (SUs) [8]. PUs refer to users who are initially granted frequency bands and are willing to share resources with other users; SUs refer to other users who are allowed to use spectrum per sharing rules. Through the programmed digital processing engine, the CR device can perceive the surrounding spectrum environment and correct wireless parameters accordingly, such as center frequency, bandwidth, transmission power, etc. Among numerous researches, dynamic spectrum access (DSA) makes it possible to reuse the same spectrum bands between primary and secondary users [9]. In DSA, the SUs opportunistically access the spectrum holes which are temporarily not occupied by licensed PUs [10]. The workflow of SUs can be simply summarized as repeatedly operating the following 3 steps:

1) **Detection.** The SUs should confirm the channel status of the PUs at startup. The detection step is the core mission of spectrum sensing.
2) **Decision.** After detecting the available frequency bands, the CR network needs to determine which free frequency bands are most suitable for use according to SU's service quality requirements and determine the transmission parameters after selecting the channel. The decision step can be regarded as the final output of spectrum sensing module for DSA.
3) **Access.** The SUs generate the waveforms corresponding to the PUs' channels and opportunistically switch to the unoccupied channel detected in step 1 for use according to SU's service quality requirements and determine the transmission parameters after selecting the channel. Successful access is the final aim that a spectrum sensing module should serve.

Spectrum sensing plays a fundamental role in DSA because it is vital to guarantee the priority of the PUs in accessing the spectrum anytime [11]. The SUs should keep alternating between spectrum sensing and data transmission. Once the PUs start accessing, SUs should immediately release the corresponding channel and switch to another idle channel.

Over the past 20 years, research into spectrum sensing techniques has made significant progress, following a constant theme of achieving faster and faultless occupancy detection and characteristics on a broader spectrum of interest. At its early stage, spectrum sensing studies mainly focus on

Manuscript received December 13, 2020.
Manuscript revised February 23, 2021.
Manuscript publicized April 26, 2021.

[†]The authors are with the Institute for Communication Systems, Home of 5GIC and 6GIC, University of Surrey, UK.
a) E-mail: yue.gao@surrey.ac.uk

DOI: 10.1587/transcom.2020DSI0002

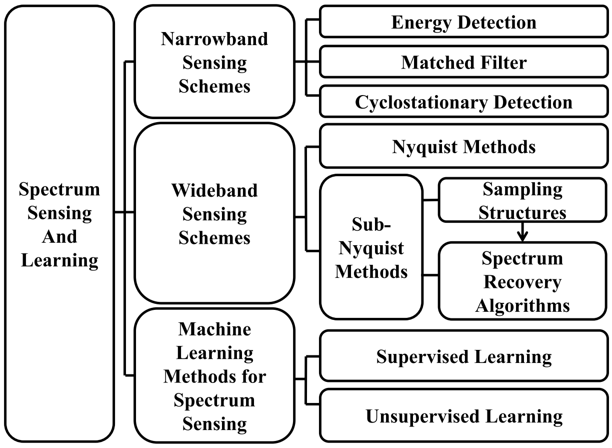

Fig. 1 Categories of spectrum sensing and learning techniques.

fundamental decision-making mechanism and distinguishing signal components from noise background in narrowbands. With the development of communication technology, the wireless signals' bandwidth has become higher and higher, putting forward CR devices requirements to work efficiently under wideband. The sub-Nyquist sampling-reconstruction technique based on compressed sensing (CS) theory has been widely studied, taking advantage of broadband signals' sparse frequency domain characteristic. A variety of compressed sampling structures have been proposed and realized from theory to practice. In terms of reconstruction algorithms, several studies are also committed to using lower complexity to achieve more accurate spectrum reconstruction. Considering the CR network itself has the characteristics of the free configuration of parameters and flexibility working in versatile environments, machine learning, as a research hotspot in recent years, has been introduced in CR to address the problem of complex system models [12]. A series of research has been conducted on spectrum sensing based on machine learning to increase accuracy and efficiency.

Following the development process mentioned above, we provide a brief overview of the mentioned developments on spectrum sensing and learning techniques for the single cognitive radio user in the rest of this paper, as shown in Fig. 1. In Sect. 2, narrowband spectrum sensing methods and basic decision-making mechanisms are introduced. In Sect. 3, we emphatically surveyed the sub-Nyquist sampling and spectrum recovery methods for wideband sensing. The main machine learning methods introduced to improve sensing performance are concluded briefly in Sect. 4, followed by the conclusion and our prospect of future challenges on spectrum sensing research in Sect. 5.

2. Narrowband Sensing Schemes

The detection of spectrum holes can be regarded as a problem based on binary assumptions: H_0 means PU does not exist, and H_1 means PU exists. Based on a certain standard, CR device makes a decision between two hypotheses:

$$\begin{cases} \mathcal{H}_0 : x(n) = w(n) & , n = 1, 2, ..., N \\ \mathcal{H}_1 : x(n) = s(n) + w(n) & , n = 1, 2, ..., N \end{cases} \tag{1}$$

where $x(n)$ denotes the digitized signal received at SU side, $s(n)$ and $w(n)$ are the sampled value of signal of interest and additive noise, respectively.

Accuracy is an important criterion of spectrum sensing performance. The key indicators to measure accuracy include detection probability P_d and false alarm probability P_f, which are defined as follows:

$$\begin{aligned} P_d &= \Pr\{\mathcal{H}_1 | \mathcal{H}_1\} \\ P_f &= \Pr\{\mathcal{H}_1 | \mathcal{H}_0\} \end{aligned} \tag{2}$$

Usually, it is required that the SUs has the least impact on regular communications of the PUs. Therefore, the primary requirement is to ensure that the possibility of the CR device misjudging an active channel as an idle channel is as small as possible, that is, P_d is close to 1. Secondly, P_f is required to be as small as possible to achieve higher spectrum utilization efficiency.

There are three basic techniques for local narrowbands perception: energy detection, matched filter detection and cyclostationary feature detection.

2.1 Energy Detector

In energy detection, the energy $D(x)$ of the received signal is measured and compared to a predefined threshold T.

$$D(x) = \frac{1}{N} \sum_{n=0}^{N-1} x^2(n) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} T. \tag{3}$$

If the energy of the received signal exceeds the threshold, it is determined that the PU occupies the channel, otherwise the channel is idle. The energy detection technology has a simple structure, low complexity, and no prior knowledge of PUs [13]. However, it is susceptible to noise power uncertainty and cannot distinguish between noise and signal [14]. Based on Eq. (3), expected improvements include double threshold detection method and dynamic threshold detection method [15], [16].

2.2 Matched Filter

The matched filter detection technique assumes that the relevant attributes of the PU signal are known in advance by SU [17]. For example, modulation type and sequence, pulse shape and data format. The frequency response of the matched filter detector is proportionally weighted to the complex conjugate of the transmitted signal spectrum $S(f)$, namely

$$H(f) \propto S^*(f), \tag{4}$$

where * refers to complex conjugate operation. The filter process is usually realized by mixing the received signal with the known PU signal, and samples the mixer output at the bit rate. The rest decision process is similar to the energy detector.

Compared with the energy detector, the matched filter can provide the maximum SNR for a given signal and improve the detection probability. Due to the coherence, the matched filter may require less time and receive signal samples to obtain higher processing gain. However, if the prior information, i.e. $S(f)$, cannot be obtained accurately, th detection performance will seriously degrade. In addition, it is very difficult to achieve accurate signal synchronization, so this method is not very practical [18].

2.3 Cyclostationary Detection

Cyclostationary detection utilizes the cyclostationary characteristics of the modulated signal to detect the existence of an authorized signal. The basic idea is to use the difference in the statistical characteristics of noise and PU signals to achieve spectrum detection.

A signal is called to be cyclostationary with period T_0 if its expectation value $\mathbb{E}[s(t)]$ and autocorrelation function $R_s(t,\tau) = \mathbb{E}[s(t-\tau/2)s^*(t+\tau/2)]$ show a cyclically stable change statistically, namely

$$\begin{cases} \mathbb{E}[s(t+T_0)] = \mathbb{E}[s(t)] \\ R_s(t+T_0,\tau) = R_s(t,\tau) \end{cases}, \tag{5}$$

The autocorrelation of a signal component can be expanded as Fourier series

$$R_s(t,\tau) = \sum_{\alpha} R_s^{\alpha}(\tau) e^{j2\pi\alpha t}, \tag{6}$$

where $\alpha = m/T_0$ ($m \in \mathbb{Z}$) and the Fourier coefficient $R_s^{\alpha}(\tau)$ is also referred to as cyclic autocorrelation function with respect to τ. The cyclic spectrum $S_x^{\alpha}(f)$ can be obtained by calculating the Fourier transform of $R_s^{\alpha}(\tau)$, namely

$$S_s^{\alpha}(f) = \int_{-\infty}^{\infty} R_s^{\alpha}(\tau) e^{-j2\pi f\tau} \mathrm{d}\tau, \tag{7}$$

where α is called the cyclic frequency and f is called the angular frequency. While $a = 0$, the cyclic power spectral density is the power spectral density. According to the irrelevance of noise and signal, we can get

$$S_x^{a}(f) = S_s^{a}(f) + S_w^{a}(f). \tag{8}$$

Since the noise signal is not cyclostationary [19], [20], when $a \neq 0$,

$$S_x^{a}(f) = \begin{cases} 0 & \longrightarrow H_0 \\ S_s^{a}(f) & \longrightarrow H_1 \end{cases}. \tag{9}$$

Therefore, at a lower signal-to-noise ratio (SNR), cyclostationary detection can use the autocorrelation function to calculate the second-order statistics of the signal, thereby realizing effective detection of the primary user. Cyclostationary detection technology is based on the cyclic redundancy of sampling and modulation signals, which can extract the PU signal from the noise, and performs well under low SNR [21]. However, the computational complexity of this algorithm is relatively high, and the prior knowledge of PU is required [22].

3. Compressive Spectrum Sensing for Wideband Signals

The development of 5G has brought higher requirements to CR devices. The enhanced mobile broadband (eMBB), as one of the three major application scenarios of 5G, pursues higher speeds by adopting larger bandwidths and increasing baseband data rate. Another prominent feature of 5G is the utilization of millimeter wave (mmWave) frequency bands, which allocated to 5G in most countries are concentrated in 24 GHz/28 GHz/39 GHz/60 GHz. Taking 28 GHz mmWave as an example, the maximum bandwidth is 1.4 GHz, which is more than ten times larger than the bandwidth of about 100 MHz for 800 MHz~2600 MHz signals currently used by 4G LTE. FCC committee members stated at MWCA2018 that as networks become denser in the 6G era, blockchain-based DSA technology is a trend.

Transplanting traditional sensing technology to sense a broader spectrum puts forward higher requirements on the analog-to-digital converter (ADC). However, high-speed ADC is expensive, complex and energy-intensive, which is not suitable for CR devices [23]. A large part of the research on wideband spectrum sensing (WSS) based on dividing the wideband into multiple narrowbands (also called multi-band sensing or multi-channel sensing) cannot effectively track the spectrum usage in real-time [24], [25].

The CS method proposed in recent years takes advantage of the signal spectrum's sparse nature in the frequency domain and can recover the signal spectrum from the sub-Nyquist sampling points [26]. The core of CS theory is: if a signal is sparse or compressible on a specific orthogonal basis, then the signal can be successfully recovered from a small amount of linear random measurement values [27]. For wideband multi-band signals that are usually sparse in the frequency domain, the two most attractive features of using CS are:

1) Compressed sampling at sub-Nyquist rate can be achieved;
2) Sampling and compression can be performed simultaneously, and The redundant information in the signal sampling is discarded.

The advantage is that the compressed sampling data can be obtained directly from the simulated continuous-time signal. Then the compressed data can be processed in the DSP unit using convex optimization or matching pursuit methods [28]. Compared to the Nyquist resolutions for WSS, compressive spectrum sensing (CSS) shifts the burden of high-speed ADCs to back-end spectrum recovery algorithms [29], [30].

WSS's signal models include multi-band or line spectrum signal models, sparse or non-sparse signals, and known or unknown carrier frequencies. For different signal models, the minimum sub-Nyquist sampling frequency required to reconstruct the spectrum or power spectrum is also different [31], [32]. Using the statistical characteristics of stationary signals, Yen et al. studied the power spectrum reconstruction problem under non-sparse signals based on the multicoset sampling scheme. They deduced the necessary and sufficient conditions for perfect reconstruction of the power spectrum in noise-free case [33]. D. Cohen et al. Provides a general framework based on the power spectrum perception based on Nyquist samples and proposes the power spectrum reconstruction algorithm required to achieve the minimum sampling rate [34]. The minimum sampling rate required for perfect reconstruction of the power spectrum without noise can be concluded as follows.

1) **Non-sparse spectrum.** When the spectrum is not sparse, the minimum sampling rate required is half of the Nyquist sampling rate.
2) **Sparse spectrum and known support.** The frequency spectrum is sparse, and when the carrier frequency is known, the minimum sampling rate required is half of the Landau rate, i.e. the Lebesgue measure of the occupied bandwidth [35].
3) **Sparse spectrum and blind recovery.** When the frequency spectrum is sparse and the carrier frequency is unknown (blind case), the minimum sampling rate required is the Landau rate [36].

Usually two steps are required to perform CSS. The first step is random sampling. The sparse observation matrix generally needs to satisfy restricted isometry property (RIP), null space property (NSP), spark† constraints and coherence constraints [37]–[39]. Several mainstream compressive sampling schemes will be reviewed in Sect. 3.1. The second step is spectrum reconstruction, mainly including convex optimization and greedy algorithms, which will be briefly reviewed in Sect. 3.2.

3.1 Compressive Sampling Schemes

In practice, it is challenging to construct a completely random measurement matrix in the hardware circuit. Therefore, a partially-random sensing matrix has been widely studied [40], [41]. Several sub-Nyquist sampling circuits have been proposed in practice [42], such as random demodulator, modulated wideband converter (MWC) and multicoset sampler. These designs are widely studied because of their relatively simple realizability. Random demodulator and MWC achieve partial randomness through the mixing of pseudo-random sequences, while multicoset sampler achieves partial randomness through different sampling delays. Based on these designs, compressed sampling can be realized upon traditional sampling circuits with low-speed ADCs. Software-defined radio (SDR) also provides the existing physical layer foundation for realizing the spectrum sensing. With the technological development of antennas, front-ends, analog-to-digital conversion and digital signal processing, CSS functions in the physical layer have been realized in some pioneering research and will be discussed below.

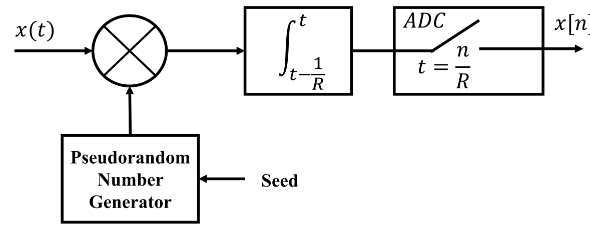

Fig. 2 System diagram of random demodulator.

3.1.1 Random Demodulator

Proposed in 2010, the random demodulator consists of a multiplier, a pseudo-random sequence generator, a low-pass filter and a sub-Nyquist rate ADC. The input signal is firstly multiplied with a Nyquist-rate pseudo-random sequence, where the signal spectrum is convoluted to the dispersive-distributed spectrum of the pseudo-random sequence. After filtering, only the low-frequency components are kept, but the spectrum information can still be recovered from low-rate samples $x[n]$ (Fig. 2) [43].

Random demodulator has been widely referred to in the wideband spectrum sensing to reduce the sampling rate requirement and the burden of digital signal processing. Candes et al. have present a non-uniform sampling (NUS) system embedded in a custom sample-and-hold chip for wideband compressive spectrum sensing [44]. The NUS uses a pseudo-random bit sequence generator to discard some of the Nyquist sampling points by controlling ADC's output switch. With 236 Msps average sample rate, the implementation can achieve adequate effective instantaneous bandwidth (EIBW) of 800 MHz to 2 GHz with up to 100 MHz information bandwidth. However, a random demodulator is more sensitive to the signal model and has a better recovery performance on the line-spectrum signal. When there is a model mismatch, the recovery result will become erroneous. On the hardware aspect, the original purpose of mixers was to up-convert or down-convert single-frequency signals. In contrast, in a random demodulator, the mixer is applied to mix a multi-band signal with a pseudo-random sequence. Due to the mixer's abnormal use, a large number of harmonics will be introduced at the mixer's output inevitably, which also limits the promotions of the random demodulator.

3.1.2 Modulated Wideband Converter

In 2010, Yonina C. Eldar et al. proposed the modulated wideband converter (MWC) and the corresponding recovery algorithms. MWC scheme starts from the classic Fourier analysis to build the relationship between the measured

†The spark of a $m \times n$ matrix A is the smallest number k such that there exists a set of k columns in A which are linearly dependent.

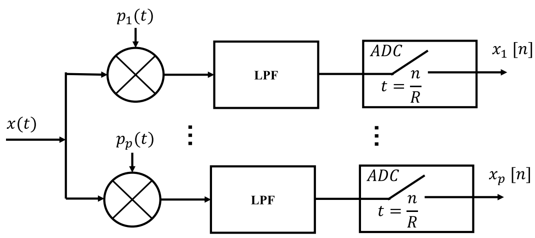

Fig. 3 System diagram of modulated wideband converter.

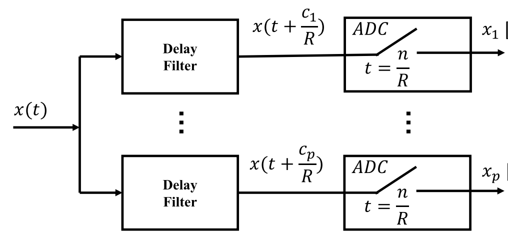

Fig. 4 System diagram of multicoset sampler.

value and the signal of the system, using the CS recovery algorithm to complete the reconstruction of the signal [45], [46].

Figure 3 describes the structure of the MWC, including multiple parallel channels sampled at the sub-Nyquist rate. MWC uses a structure similar to random demodulators in parallel. Before sampling, the input signal $x(t)$ is split into p ways and then mixed with p different pseudo-random sequence $p_1(t)$ to $p_p(t)$, respectively. This operation moves the frequency spectrum of the input signal to the low-frequency band. Then a low-pass filter array is applied to filter out high-frequency components, and the filtered signals are sampled through a low-speed ADC array.

The time-domain reconstruction model of MWC can be attributed to the multi-measurement vector (MMV) problem, which has been proved to improve the ability to successfully recover the sparse solution compared with the single measurement vector (SMV) case introduced by the random demodulator [47]–[49].

The MWC-type hardware implementation has been realized on board as Xampling analog-to-digital converter in 2010 [50]. The circuit contains an analog power splitter front end and four parallel mixing&filtering instances, achieving compressive sampling of 2 GHz-band signal with 120 MHz arbitrary spectrum occupancy. The average sample rate is as low as 280 MHz, namely, 14% of the Nyquist rate and 2.33 times the Landau rate. Based on the circuits, a CSS platform is presented with an external FPGA-based pseudo-random sequence generator and SDR-based digital signal processor [46], [51]. An on-chip realization of MWC-type sampler is presented as random modulator pre-integrator (RMPI) [52]. The RMPI prototype is integrated on a millimeter-scale IBM 90 nm digital CMOS chip with eight mixing and filtering signal channels. Cooperated with external ADCs, it can achieve up to 2 GHz EIBW with 320MSPS aggregate digitization rate [53].

3.1.3 Multicoset Sampler

The multicoset sampling method can be implemented on a time interleaving ADC (TI-ADC) platform. By controlling the sampling delay of each ADC, a compressed sampling perception matrix can be constructed. Figure 4 describes the structure of multicoset sampler. Including p-channel delay filters and p-channel low-speed ADCs. Each delay filter apply an exclusive delay c_i/R $(i = 1, ..., p)$ to the original signal. In the signal acquisition process, the signal to be measured enters the ADC for sampling through different delay filters with randomly-set delays. Therefore, from each channel, a subset of the Nyquist samples is acquired, and all the p subsets form a compressed subset chosen non-uniformly from the Nyquist samples.

Like the reconstruction process of MWC, the reconstruction of a multicoset sampler can be divided into two steps. First, the MMV model is constructed through the covariance matrix of the p-channel sampling data. The MMV recovery algorithm is then used to solve the support set of the wideband sparse spectrum.

The real-time multi-gigahertz processing platform for muticoset sampler and recovery algorithms working on the mmWave band is realized based on SDR systems [54]. Both the transmitter and receiver have modular configurable hardware operating at mmWave frequency centred at 28.5 GHz. Psuedo-random symbols modulated by 64-QAM and Verizon 5G OFDM waveform spanning the bandwidth of 100 MHz can be transmitted with multiple component carriers of which the frequencies can be reconfigured. A single high-speed ADC samples the baseband signal at the receiver by a 3.072 GHz sampling clock. The multicoset sampler behaviour is simulated by discarding a subset of raw digital samples acquired by the single 3.072G ADC, effectively forming parallel signal branches. The platform is configurable on parameters like active channels and the center frequency at the Tx side and the co-set number, average sample rate, channel delays and window length at the Rx, providing an ideal testing environment for multicoset sampling and recovery performance under different configurations.

3.2 Spectrum Recovery

Given the observation matrix $\mathbf{A}$ and the sparse matrix ϕ, the original spectrum can be reconstructed by solving the underdetermined equations

$$\arg\min \ \|\mathbf{X}\|_{2,1} \ \text{ s.t. } \ \|\mathbf{Y} - \mathbf{A}\phi\mathbf{X}\|_2 < \epsilon, \tag{10}$$

where $\mathbf{X}$ and $\mathbf{Y}$ refers to the original signal and the compressive measurement, respectively and ϕ is usually treated as inverse discrete Fourier transform (IDFT). The high-dimensional original signal $\mathbf{X}$ can be reconstructed accurately or with high probability from the compressive measurement $\mathbf{Y}$.

There are mainly two types of methods for solving the

Table 1 Recovery algorithms and corresponding time complexity.

Type	Algorithm	Model	Time Complexity
Optimization Algorithm	BP	SMV	$O(N^3)$
Greedy Algorithm	OMP	SMV	$O(M^4)$
	SOMP	MMV	$O((k^c)^2 NM)$
	CoSaMP	SMV	$O(NM)$
	HTP	SMV	$O(M^3 \log(k^c))$
	JB-HTP	MMV	$O(k^c NM)$

equations of such underdetermined matrices: one is the convex optimization reconstruction algorithm based on basis pursuit (BP) [55]. This type of algorithm is mainly the convex optimization algorithm based on the l_1 norm minimization constraint [56]. This type of algorithm is characterized by high signal recovery accuracy but high computational complexity, which is generally the cube of the signal dimension. Similar l_v-minimization method are proposed to reduce measurements [57].

Another type of algorithm is the greedy algorithm, including orthogonal matching pursuit (OMP) algorithm [58] for SMV model, simultaneous OMP (SOMP) algorithm [59] for MMV model, compressed sampling matching pursuit (CoSaMP) algorithm [60], hard thresholding pursuit (HTP) algorithm and joint-block HTP (JB-HTP) algorithm for joint-block sparse signal [61], [62], etc. This type of algorithms is characterized by low computational complexity, but the reconstruction effect is not as good as the convex optimization algorithm. Greedy algorithms usually require prior knowledge of signal sparsity to optimize recovery performance and minimize iteration time. In the lack of prior information, sparsity estimation methods based on Bayesian information theory are often applied to obtain an estimation of the signal support [63]. The comparison between different recovery algorithms is shown in Table 1, where each algorithm's time complexity is estimated with respect to signal length N, compressed data length M and estimated sparsity k^c. For different sensing scenario and different sub-Nyquist sampling parameters, a proper greedy algorithm should be chosen for better performance [61].

4. Learning from the Environment

During the CR system operation, its operating parameters (such as transmission power, perception strategies, coding methods, modulation methods, communication protocols, etc.) and the surrounding electromagnetic environment (channel fading, multipath effects, changes in signal-to-noise ratio, etc.) are often in change [64], [65]. This makes it difficult to express the entire system model with simple models, which affects the accuracy of spectrum sensing results [66]. Compared with traditional spectrum sensing algorithms, the most significant advantage of machine learning is learning from data and calculating the parameters required for spectrum sensing.

Spectrum sensing based on machine learning can be regarded as a problem using machine learning algorithms to find cognitive radio system models and parameters [67]. Suppose the prior information about the PU signal is known. In that case, the supervised learning method can better play the guiding role of prior knowledge in constructing the cognitive model and training a high-performance spectrum sensing model. In an unfamiliar electromagnetic environment, the spectrum sensing technology based on unsupervised learning can explore the surrounding environment's characteristics through autonomous learning and calculate the parameters required by the spectrum sensing system model adaptively to avoid prior information. The PU signal is detected in the scene. Therefore, this article will classify and discuss the machine learning algorithms in spectrum sensing from two aspects: supervised learning and unsupervised learning.

4.1 Supervised Learning

Supervised learning algorithms need to use labeled data for training, mainly including k nearest neighbours (KNN), support vector machine (SVM) and artificial neural network (ANN).

KNN is one of the simplest models in supervised learning. The data points with similar characters are generally in close proximity according to a specific distance metric, regardless of the distribution of the data points [68]. The KNN first divides the training data set into several groups, where each group corresponds to a unique decision or action. When a new signal arrives, it will be classified in a specific group, and the proper decision will be made. For example, the received PU signal's power strength is used as the core radio environment data for the spectrum detection or even PU localization in CR networks [69], [70].

When the signal of the learning data set is not linearly separable, KNN is no longer applicable. Using kernel functions, the SVM algorithm maps the data from its original space to a higher dimension where the data becomes linearly separable. The SVM algorithm is based on the structural risk minimization criterion. By adding a regularization term or penalty term representing the complexity of the model to the empirical risk, the over-fitting problem is avoided to a certain extent, and it shows superior performance, especially for relatively small training examples [71]. SVM model for medium access control (MAC) protocol identification has been proposed to enable the CR devices to distinguish four types of MAC protocol, namely TDMA, CSMA/CA, pure ALOHA and slotted ALOHA, of any existing transmissions to avoid potential interference to PUs and existing SUs [72]. Under a low-SNR scenario and limited training data, SVM is proved to have high efficiency in successive spectrum hole detection.

ANN is an adaptive system, which has been widely used in cognitive radio. It can simulate arbitrary nonlinear mapping by modeling the relationship between input and output. The basic mathematical expression can be expressed as

$$o = f(\sum_{n=1}^{N} w_n x_n) \tag{11}$$

where $x_1,x_2,...,x_N$ are inputs of ANN and $w_1,w_2,...,w_N$ are the relative weights learned from the labelled data. The proper decision or action towards new signals will be decided by its output o. The ANN algorithm is based on the empirical risk minimization criterion. Training network parameters can reduce the metric distance between the network output and the training data label to minimize the empirical risk. A related approach has shown that multi-layer perceptron can effectively reduce sensing energy and improve spectrum utilization [73]. The convolutional-neural-network (CNN)-based spectrum sensing model is proven to provide higher detection probability than cyclostationary detection in the −20 dB range[74].

4.2 Unsupervised Learning

In CR, SU needs to operate on any available frequency band, any time and any place, so it is very likely that the radio frequency environment's working conditions, such as noise or interference level, noise distribution or user traffic, are known in advance [75]. Therefore, the CR device must learn independently in an unknown RF environment without training samples and independently explore the radio environment in which it is located, then dig out the observed data laws to find out the possible spectrum holes. Therefore, compared to supervised learning, unsupervised learning is more suitable for cognitive radio application scenarios [76]–[78].

The unsupervised learning classification algorithm is also known as the clustering algorithm [79]. It can automatically divide samples into multiple disjoint clusters according to their inherent properties without requiring labelled training data set. Commonly used unsupervised learning algorithms include the K-means algorithm and Gaussian mixture model (GMM) algorithm.

The K-means algorithm's goal is to find a specific classification method so that the classified data has a higher degree of similarity within the class. For data with ordered attributes, the optimization strategy is to minimize the sum of Minkowski distance within the classified cluster, namely

$$\arg\min_{C} \{ \sum_{x_i,x_j \in C} \mathrm{dist}_m(x_i, x_j)\} \tag{12}$$

where $\mathrm{dist}_m(x_i, x_j) = (\sum_{k=1} |x_{ik} - x_{jk}|^l)^{\frac{1}{l}}$ denotes the Minkowski distance between x_i and x_j, l is integer and usually picked as 2 (Euclidean distance). The smaller the Minkowski distance is, the more similar the data sets are. An empirical mode decomposition and k-means based approach has been proposed to remove the redundant noise components in the nonstationary or nonlinear sampling signal and shows improvement in sensing performance [80]. The K-means algorithm built on the minimum description length principle can further eliminate the false alarm rate [81].

Table 2 Different machine learning algorithms and their features.

Category	Algorithm	Characteristics
Supervised Learning	KNN	One-to-one mapping Applicable for linearly separable data
	SVM	One-to-one mapping Applicable for linearly non-separable data
	ANN	Better mapping relationship between data and action Overfitting problem
Unsupervised Learning	K-means	Non-gradient optimization algorithm Hard decision Requires relatively independent input variables Sensitive to initial setup
	GMM	Soft decision Requires knowledge of data distribution Overfitting problem

Unlike the K-means algorithm, GMM uses Gaussian distribution to describe the distribution of data in clusters. It assumes that each cluster corresponds to a Gaussian probability distribution. For a sample of data, each cluster may have a corresponding generation probability. The posterior likelihood will determine the cluster division of the data. The posterior probability gives the probability that each Gaussian model produces the sample data. The most considerable posterior probability model can be considered the cluster that the sample data should be divided into. In the unsupervised case, the GMM model's training can generally be realized based on the expectation-maximization (EM) algorithm [69], [82]. For better comparison, the commonly used machine learning algorithms in spectrum sensing mentioned above and their features are summarized in Table 2.

5. Conclusion and Future Challenges

This paper has tried to provide a brief overview of spectrum sensing techniques for cognitive radio users. Following the demand driven by wireless communication development, we started from the fundamental narrow-band detection and decision mechanism. Afterwards, compressive spectrum sensing is investigated from theory to practice as a promising approach enabling CR devices to work in wideband scenario. Moreover, the recent advancements in machine-learning-based spectrum sensing have been characterized, which has provided CR devices with better adaptivity and higher flexibility under complex radio environments.

Still, the performance demands placed on spectrum sensing will create many different challenges. The SU cannot perform spectrum sensing while sending data, and the sensing period determines the degree of degradation of PU performance. It is desirable to spend as little time as possible for spectrum sensing to improve data transmission throughput and increase spectrum monitoring frequency to prevent PU from being affected. Therefore, a conflict always exists between the CR data transmission rate and the spectral sensing time resolution, and the situation is even aggravated when the SU number increases. Therefore, a corresponding spectrum management mechanism is required to limit the secondary user's transmission activity and power based on the primary receiving user's detection sensitivity.

Under a wideband sensing scenario, the performance of CSS based on a single node under low SNR is still not ideal. When the SNR is lower than 5 dB, the performance of blind sensing basically cannot meet the requirements of practical applications [83]. Therefore, it is a topic worthy of study to achieve a high probability reconstruction of the spectrum support without increasing the hardware complexity.

Spectrum reconstruction based on greedy algorithm requires prior knowledge of spectrum sparsity as input. However, in many application backgrounds, the spectrum support is unpredictable, and the communication parameters (such as modulation mode, transmit power, data rate, etc.) of each PU multiple numbers are different. In the case of blind sampling, the CSS algorithm must adjust the necessary parameters for other channels and estimate the spectrum support, causing a more serious computational burden.

Additionally, the occupancy rate of the spectrum is often changing. If the average compressed sampling rate cannot reach the required minimum threshold, the detection will fail. Suppose a higher compressed sampling rate is always used (for example, using more channels in the multicoset sampler). In that case, it will cause a waste of resources and significantly increase the cognitive terminal's energy consumption. Although adaptive algorithms, such as cross-validation, give the CSS system the ability to adjust the compressed sampling rate autonomously according to the signal, the cross-validation still causes additional resource overhead for parameter estimation [57], [84].

The sparsity of spectrum utilization is a prerequisite for the implementation of compressed sensing methods. However, if many CR users share a broadband spectrum with the PUs, this assumption may not hold. Therefore, how to distinguish PU from many SUs is a coexistence problem in CSS.

For the learning-based studies, the radio models used in many research works are still too simple to be applied in a real environment. In practical applications, the noise model and the received signal strength distribution are difficult to obtain accurately. It is necessary to comprehensively consider the wireless environment characteristics such as transmitter power leakage, spectral correlation, transmission path loss, channel multipath loss, and burst noise. Besides, the learning and training data of existing research is mostly collected in a short period. With more realistic research scenarios and more complex models, it is necessary to collect and organize data on a longer time scale for specific frequency bands.

Acknowledgments

The work in this paper was supported by the Engineering and Physical Sciences Research Council in United Kingdom, under the Grant EP/R00711X/2.

References

[1] Spectrum needs for the terrestrial component of IMT in the frequency range between 24.25 GHz and 86 GHz, 2016-09-22, ITU-R WP5D Contribution 259.
[2] G.F. Elmasry, "Dynamic spectrum management for cellular 5G systems," Dynamic Spectrum Access Decisions: Local, Distributed, Centralized, and Hybrid Designs, pp.93–116, John Wiley & Sons, 2020.
[3] U. Herzog, A. Georgakopoulos, I. Belikaidis, P. Demestichas, S. Diaz, Ó. Carrasco, F. Miatton, K. Moessner, and V. Frascolla, "Quality of service provision and capacity expansion through extended-DSA for 5G," 2016 European Conference on Networks and Communications (EuCNC), pp.200–204, 2016.
[4] S. Mumtaz, A. Al-Dulaimi, V. Frascolla, D. Niyato, and K. Briggs, "Dynamic spectrum management for 5G," IEEE Wireless Commun., vol.24, no.5, pp.12–13, 2017.
[5] C.B. Papadias, T. Ratnarajah, and D.T. Slock, Spectrum Sharing: The Next Frontier in Wireless Networks, John Wiley & Sons, 2020.
[6] B. Moon, "Dynamic spectrum access for Internet of things service in cognitive radio-enabled LPWANs," Sensors, vol.17, no.12, p.2818, 2017.
[7] R. Tandra and A. Sahai, "Fundamental limits on detection in low SNR under noise uncertainty," Wireless Networks, Communications and Mobile Computing, 2005 International Conference on, 2005.
[8] G.K. Papageorgiou, K. Voulgaris, K. Ntougias, D.K. Ntaikos, M.M. Butt, C. Galiotto, N. Marchetti, V. Frascolla, H. Annouar, A. Gomes, A.J. Morgado, M. Pesavento, T. Ratnarajah, K. Gopala, F. Kaltenberger, D.T.M. Slock, F.A. Khan, and C.B. Papadias, "Advanced dynamic spectrum 5G mobile networks employing licensed shared access," IEEE Commun. Mag., vol.58, no.7, pp.21–27, 2020.
[9] G.F. Elmasry, "DSA and 5G adaptation to military communications," Dynamic Spectrum Access Decisions: Local, Distributed, Centralized, and Hybrid Designs, pp.117–126, John Wiley & Sons, 2020.
[10] Q. Zhao and B.M. Sadler, "A survey of dynamic spectrum access," IEEE Signal Process. Mag., vol.24, no.3, pp.79–89, 2007.
[11] Y. Xing, R. Chandramouli, S. Mangold, and S.S. N, "Dynamic spectrum access in open spectrum wireless networks," IEEE J. Sel. Areas Commun., vol.24, no.3, pp.626–637, 2006.
[12] S. Mosleh, Y. Ma, J.D. Rezac, and J.B. Coder, "Dynamic spectrum access with reinforcement learning for unlicensed access in 5G and beyond," 2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring), pp.1–7, 2020.
[13] Z. Li, B. Chang, S. Wang, A. Liu, F. Zeng, and G. Luo, "Dynamic compressive wide-band spectrum sensing based on channel energy reconstruction in cognitive internet of things," IEEE Trans. Ind. Inf., vol.14, no.6, pp.2598–2607, 2018.
[14] R. Tandra and A. Sahai, "SNR walls for signal detection," IEEE J. Sel. Top. Signal Process., vol.2, no.1, pp.4–17, 2008.
[15] Z. Jiang, Z. Xu, F. Wang, B. Huang, and Z. Bo, "Double threshold energy detection of cooperative spectrum sensing in cognitive radio," International Conference on Cognitive Radio Oriented Wireless Networks & Communications, 2008.
[16] K. Kim, Y. Xin, and S. Rangarajan, "Energy detection based spectrum sensing for cognitive radio: An experimental study," 2010 IEEE Global Telecommunications Conference GLOBECOM 2010, 2011.
[17] D. Cabric, S.M. Mishra, and R.W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, 2004., pp.772–776, IEEE, 2004.
[18] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," IEEE Commun. Surveys Tuts., vol.11, no.1, pp.116–130, 2009.
[19] M. Oner and F. Jondral, "Cyclostationarity-based methods for the

extraction of the channel allocation information in a spectrum pooling system," Proc. 2004 IEEE Radio and Wireless Conference (IEEE Cat. no. 04TH8746), pp.279–282, IEEE, 2004.
[20] D. Cohen and Y.C. Eldar, "Sub-nyquist cyclostationary detection for cognitive radio," IEEE Trans. Signal Process., vol.65, no.11, pp.3004–3019, 2017.
[21] T. Liu, T. Qiu, and S. Luan, "Cyclic frequency estimation by compressed cyclic correntropy spectrum in impulsive noise," IEEE Signal Process. Lett., vol.26, no.6, pp.888–892, 2019.
[22] Z. Tian, Y. Tafesse, and B.M. Sadler, "Cyclic feature detection with sub-nyquist sampling for wideband spectrum sensing," IEEE J. Sel. Top Signal Process., vol.6, no.1, pp.58–69, 2011.
[23] H. Mamaghanian, N. Khaled, D. Atienza, and P. Vandergheynst, "Design and exploration of low-power analog to information conversion based on compressed sensing," IEEE J. Emerg. Sel. Topics Circuits Syst., vol.2, no.3, pp.493–501, 2012.
[24] H. Sun, A. Nallanathan, C.X. Wang, and Y. Chen, "Wideband spectrum sensing for cognitive radio networks: A survey," IEEE Wireless Commun., vol.20, no.2, pp.74–81, 2013.
[25] X. Zhang, Y. Ma, H. Qi, Y. Gao, Z. Xie, Z. Xie, M. Zhang, X. Wang, G. Wei, and Z. Li, "Distributed compressive sensing augmented wideband spectrum sharing for cognitive IoT," IEEE Internet Things J., vol.5, no.4, pp.3234–3245, 2018.
[26] Z. Tian and G.B. Giannakis, "Compressed sensing for wideband cognitive radios," 2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP'07, pp.IV-1357–IV-1360, IEEE, 2007.
[27] M.F. Duarte and Y.C. Eldar, "Structured compressed sensing: From theory to applications," IEEE Trans. Signal Process., vol.59, no.9, pp.4053–4085, 2011.
[28] S.K. Sharma, E. Lagunas, S. Chatzinotas, and B. Ottersten, "Application of compressive sensing in cognitive radio communications: A survey," IEEE Commun. Surveys Tuts., vol.18, no.3, pp.1838–1860, 2016.
[29] Y.C. Eldar, Sampling Theory: Beyond Bandlimited Systems, Cambridge University Press, 2015.
[30] M. Mishali and Y.C. Eldar, "Sub-nyquist sampling," IEEE Signal Process. Mag., vol.28, no.6, pp.98–124, 2011.
[31] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," Sensors, vol.19, no.1, p.126, 2019.
[32] D.D. Ariananda and G. Leus, "Compressive wideband power spectrum estimation," IEEE Trans. Signal Process., vol.60, no.9, pp.4775–4789, 2012.
[33] C.P. Yen, Y. Tsai, and X. Wang, "Wideband spectrum sensing based on sub-nyquist sampling," IEEE Trans. Signal Process., vol.61, no.12, pp.3028–3040, 2013.
[34] D. Cohen and C.Y. Eldar, "Sub-nyquist sampling for power spectrum sensing in cognitive radios: A unified approach," IEEE Trans. Signal Process., vol.62, no.15, pp.3897–3910, 2014.
[35] H.J. Landau, "Necessary density conditions for sampling and interpolation of certain entire functions," Acta Math., vol.117, no.1, pp.37–52, 1967.
[36] S. Gleichman and Y.C. Eldar, "Blind compressed sensing," IEEE Trans. Inf. Theory, vol.57, no.10, pp.6958–6975, 2011.
[37] S. Foucart and H. Rauhut, A Mathematical Introduction to Compressive Sensing, Springer, 2013.
[38] A.M. Tillmann and M.E. Pfetsch, "The computational complexity of the restricted isometry property, the nullspace property, and related concepts in compressed sensing," IEEE Trans. Inf. Theory, vol.60, no.2, pp.1248–1259, 2014.
[39] D.L. Donoho and M. Elad, "Optimally sparse representation in general (nonorthogonal) dictionaries via ℓ^1 minimization," Proc. National Academy of Sciences, vol.100, no.5, pp.2197–2202, 2003.
[40] M. Rudelson and R. Vershynin, "On sparse reconstruction from fourier and gaussian measurements," Commun. Pure Appl. Math., vol.61, no.8, pp.1025–1045, 2010.
[41] H. Rauhut, J. Romberg, and J.A. Tropp, "Restricted isometries for partial random circulant matrices," Appl. Comput. Harmon. Anal., vol.32, no.2, pp.242–254, 2012.
[42] S.R. Becker, Practical Compressed Sensing: Modern Data Acquisition and Signal Processing, Ph.D. thesis, California Institute of Technology, 2011.
[43] J.A. Tropp, J.N. Laska, M.F. Duarte, J.K. Romberg, and R.G. Baraniuk, "Beyond nyquist: Efficient sampling of sparse bandlimited signals," IEEE Trans. Inf. Theory, vol.56, no.1, pp.520–544, 2009.
[44] M. Wakin, S. Becker, E. Nakamura, M. Grant, E. Sovero, D. Ching, J. Yoo, J. Romberg, A. Emami-Neyestanak, and E. Candes, "A nonuniform sampler for wideband spectrally-sparse environments," IEEE J. Emerg. Sel. Topics Circuits Syst., vol.2, no.3, pp.516–529, 2012.
[45] M. Mishali and Y.C. Eldar, "From theory to practice: Sub-nyquist sampling of sparse wideband analog signals," IEEE J. Sel. Topics Signal process., vol.4, no.2, pp.375–391, 2010.
[46] D. Cohen, S. Tsiper, and Y.C. Eldar, "Analog-to-digital cognitive radio: Sampling, detection, and hardware," IEEE Signal Process. Mag., vol.35, no.1, pp.137–166, 2018.
[47] S.F. Cotter, B.D. Rao, K. Engan, and K. Kreutz-Delgado, "Sparse solutions to linear inverse problems with multiple measurement vectors," IEEE Trans. Signal Process., vol.53, no.7, pp.2477–2488, 2005.
[48] Y. Zhao, Y.H. Hu, and J. Liu, "Random triggering-based sub-nyquist sampling system for sparse multiband signal," IEEE Trans. Instrum. Meas., vol.66, no.7, pp.1789–1797, 2017.
[49] S. Zheng and X. Yang, "Wideband spectrum sensing in modulated wideband converter based cognitive radio system," 2011 11th International Symposium on Communications & Information Technologies (ISCIT), pp.114–119, IEEE, 2011.
[50] M. Mishali, Y.C. Eldar, O. Dounaevsky, and E. Shoshan, "Xampling: Analog to digital at sub-nyquist rates," IET Circuits Devices & Systems Iet, vol.5, no.1, pp.8–20, 2009.
[51] E. Israeli, S. Tsiper, D. Cohen, E. Shoshan, R. Hilgendorf, A. Reysenson, and Y.C. Eldar, "Hardware calibration of the modulated wideband converter," 2014 IEEE Global Communications Conference, pp.948–953, IEEE, 2014.
[52] J. Yoo, S. Becker, M. Loh, M. Monge, and A. Emami-Neyestanak, "A 100 MHz–2 GHz 12.5x sub-nyquist rate receiver in 90 nm CMOS," Radio Frequency Integrated Circuits Symposium, 2012.
[53] J. Yoo, S. Becker, M. Monge, M. Loh, and A. Emami-Neyestanak, "Design and implementation of a fully integrated compressed-sensing signal acquisition system," IEEE International Conference on Acoustics, 2012.
[54] Z. Song, H. Qi, and Y. Gao, "Real-time multi-gigahertz sub-nyquist spectrum sensing system for mmwave," Proc. 3rd ACM Workshop on Millimeter-wave Networks and Sensing Systems, pp.33–38, 2019.
[55] E.J. Candés, J.K. Romberg, and T. Tao, "Stable signal recovery from incomplete and inaccurate measurements," Commun. Pure Appl. Math., vol.59, no.8, pp.1207–1223, 2006.
[56] D.P. Palomar and Y.C. Eldar, Convex Optimization in Signal Processing and Communications, Cambridge University Press, 2010.
[57] X. Zhang, Y. Ma, Y. Gao, and W. Zhang, "Autonomous compressive-sensing-augmented spectrum sensing," IEEE Trans. Veh. Technol., vol.67, no.8, pp.6970–6980, 2018.
[58] J.A. Tropp and A.C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," IEEE Trans. Inf. Theory, vol.53, no.12, pp.4655–4666, 2007.
[59] J.A. Tropp, A.C. Gilbert, and M.J. Strauss, "Simultaneous sparse approximation via greedy pursuit," Proc. (ICASSP'05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005., pp.v-721–724, IEEE, 2005.
[60] D. Needell and J.A. Tropp, "Cosamp: Iterative signal recovery from incomplete and inaccurate samples," Appl. Comput. Harmon. Anal.,

vol.26, no.3, pp.301–321, 2009.

[61] H. Qi, X. Zhang, and Y. Gao, "Low-complexity subspace-aided compressive spectrum sensing over wideband whitespace," IEEE Trans. Veh. Technol., vol.68, no.12, pp.11762–11777, 2019.

[62] Y.C. Eldar, P. Kuppinger, and H. Bolcskei, "Block-sparse signals: Uncertainty relations and efficient recovery," IEEE Trans. Signal Process., vol.58, no.6, pp.3042–3054, 2010.

[63] W. Chen and I.J. Wassell, "A decentralized bayesian algorithm for distributed compressive sensing in networked sensing systems," IEEE Trans. Wireless Commun., vol.15, no.2, pp.1282–1292, 2015.

[64] Y. Ma, Y. Gao, C. Fu, W. Rong, Z. Xiong, and S. Cui, "TV white space spectrum analysis based on machine learning," J. Commun. Inf. Netw., vol.4, no.2, pp.68–80, 2019.

[65] H. Qi, X. Zhang, and Y. Gao, "Channel energy statistics learning in compressive spectrum sensing," IEEE Trans. Wireless Commun., vol.17, no.12, pp.7910–7921, 2018.

[66] A. Toma, A. Krayani, M. Farrukh, H. Qi, L. Marcenaro, Y. Gao, and C.S. Regazzoni, "AI-based abnormality detection at the PHY-layer of cognitive radio by learning generative models," IEEE Trans. Cogn. Commun. Netw., vol.6, no.1, pp.21–34, 2020.

[67] X. Zhou, M. Sun, G.Y. Li, and B.H.F. Juang, "Intelligent wireless communications enabled by cognitive radio and machine learning," China Commun., vol.15, no.12, pp.16–48, 2018.

[68] Z. Qin, X. Zhou, L. Zhang, Y. Gao, Y.C. Liang, and G.Y. Li, "20 years of evolution from cognitive to intelligent communications," IEEE Trans. Cogn. Commun. Netw., vol.6, no.1, pp.6–20, 2019.

[69] K.M. Thilina, K.W. Choi, N. Saquib, and E. Hossain, "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," IEEE J. Sel. Areas Commun., vol.31, no.11, pp.2209–2221, 2013.

[70] D. Li, B. Zhang, and C. Li, "A feature-scaling-based k-nearest neighbor algorithm for indoor positioning systems," IEEE Internet Things J., vol.3, no.4, pp.590–597, 2015.

[71] H. Hu, Y. Wang, and J. Song, "Signal classification based on spectral correlation analysis and SVM in cognitive radio," 22nd International Conference on Advanced Information Networking and Applications (AINA 2008), pp.883–887, IEEE, 2008.

[72] S. Hu, Y.D. Yao, and Z. Yang, "MAC protocol identification using support vector machines for cognitive radio networks," IEEE Wireless Commun., vol.21, no.1, pp.52–60, 2014.

[73] V.K. Tumuluru, P. Wang, and D. Niyato, "A neural network based spectrum prediction scheme for cognitive radio," 2010 IEEE International Conference on Communications, pp.1–5, IEEE, 2010.

[74] D. Han, G.C. Sobabe, C. Zhang, X. Bai, Z. Wang, S. Liu, and B. Guo, "Spectrum sensing for cognitive radio based on convolution neural network," 2017 10th International Congress on Image and Signal Processing, Biomedical Engineering and Informatics (CISP-BMEI), pp.1–6, IEEE, 2017.

[75] M. Bkassiny, Y. Li, and S.K. Jayaweera, "A survey on machine-learning techniques in cognitive radios," IEEE Commun. Surveys Tuts., vol.15, no.3, pp.1136–1159, 2013.

[76] M. Bkassiny, S.K. Jayaweera, Y. Li, and K.A. Avery, "Wideband spectrum sensing and non-parametric signal classification for autonomous self-learning cognitive radios," IEEE Trans. Wireless Commun., vol.11, no.7, pp.2596–2605, 2012.

[77] O. Naparstek and K. Cohen, "Deep multi-user reinforcement learning for distributed dynamic spectrum access," IEEE Trans. Wireless Commun., vol.18, no.1, pp.310–323, 2018.

[78] H.H. Chang, H. Song, Y. Yi, J. Zhang, H. He, and L. Liu, "Distributive dynamic spectrum access through deep reinforcement learning: A reservoir computing-based approach," IEEEIEEE Internet Things J., vol.6, no.2, pp.1938–1948, 2018.

[79] H. Eltom, S. Kandeepan, R.J. Evans, Y.C. Liang, and B. Ristic, "Statistical spectrum occupancy prediction for dynamic spectrum access: A classification," EURASIP J. Wireless Commun. Netw., vol.2018, no.1, pp.1–17, 2018.

[80] Y. Zhang, P. Wan, S. Zhang, Y. Wang, and N. Li, "A spectrum sensing method based on signal feature and clustering algorithm in cognitive wireless multimedia sensor networks," Advances in Multimedia, vol.2017, 2017.

[81] R. Rao, Q. Cheng, and P.K. Varshney, "Subspace-based cooperative spectrum sensing for cognitive radios," IEEE Sensors J., vol.11, no.3, pp.611–620, 2010.

[82] D. Malafaia, J. Vieira, and A. Tomé, "Adaptive threshold spectrum sensing based on expectation maximization algorithm," Physical Commun., vol.21, pp.60–69, 2016.

[83] Z. Hu, Y. Bai, M. Huang, M. Xie, and Y. Zhao, "A self-adaptive progressive support selection scheme for collaborative wideband spectrum sensing," Sensors, vol.18, no.9, p.3011, 2018.

[84] Z. Qin, J. Wang, J. Chen, and L. Wang, "Adaptive compressed spectrum sensing based on cross validation in wideband cognitive radio system," IEEE Syst. J., vol.11, no.4, pp.2422–2431, 2015.

Zihang Song received his bachelor's and master's degrees in applied physics from Beihang University. He started his PhD study in 2019 and is now with Prof. Yue Gao and Prof. Rahim Tafazolli in University of Surrey. His current research interests include millimetre-wave spectrum sensing and sub-Nyquist signal processing.

Yue Gao is a Professor and Chair in Wireless Communications at Institute for Communication Systems, Home of 5GIC and 6GIC, University of Surrey. He develops fundamental research into practice in the interdisciplinary area of smart antennas, signal processing, spectrum sharing, millimetre-wave and internet of things technologies in mobile and satellite systems. He has published over 200 peer-reviewed journal and conference papers, one book and five book chapters. He is an Engineering and Physical Sciences Research Council Fellow from 2018 to 2023.

Rahim Tafazolli is Regius Professor of Electronic Engineering, Professor of Mobile and Satellite Communications, Founder and Director of 5G Innovation Centre (5GIC), 6G Innovation Centre (6GIC) and Institute for Communication System (ICS) at the University of Surrey. He has over 30 years of experience in digital communications research and teaching. He has authored and co-authored more than 1000 research publications and is regularly invited to deliver keynote talks and distinguished lectures to international conferences and workshops. He has been named a Fellow of the Royal Academy of Engineering in 2020.