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ORIGINAL RESEARCH

Electromagnetic Spectrum Contribution in Astronomy, Health, Atmospheric, Geology and Environment Applications

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Abstract
Spectrum technologies are shaping the way our world connects, communicates, and functions. Radio nodes connect through a nearly ubiquitous wireless mesh of other nodes, access points, satellites, and base stations to support an ever-expanding panorama of applications, spanning communication, autonomous navigation and transportation, radar-based geo-sciences, soil-sciences, renewable energy, space surveillance, environment and healthcare, smart buildings and grids, precision agriculture, consumer and industrial Internet-of-Things (IoT), and other elements of the emerging smart world. This paper offers an overview on the impact of the current and future diverse applications on the radio spectrum. Specific applications to be addressed include astronomy, health, atmospheric, geosciences, and wildfire monitoring. These applications along with many other emerging applications highlight the critical need of implementation of Intelligent Radios and dynamic spectrum access techniques that enable efficient spectrum management.

Keywords Spectrum management · Interference management · Intelligent radio · Spectrumapplications

1 Introduction

The ever-expanding panorama of electromagnetic (EM) spectrum applications, spanning autonomous transportation, radar-based geosciences, renewable energy, astronomy, surveillance.The environment, healthcare, smart buildings and grids, precision agriculture, localization and security services, consumer, and industrial Internet-of-Things (IoT), and other elements of the emerging smart world demand a revolution in spectrum management [1–3]. Migration to higher frequency bands such as mm-wave, THz, and beyond will help, but is not a complete solution to spectrum scarcity. We envision a future where all wireless devices are empowered with the information, computational capability, and authority to manage their wireless spectrum access in real-time in a globally efficient, effective, reliable, and secure manner. Revolutionizing spectrum management is possible via the foundations of Intelligent Radios (IR). IR algorithms allow real time Digital Spectrum Twining (DST) and support location-based interference mitigation. IR will allow co-existence of passive and active users and devices. Such systems will not require trust from overarching government or industry entities leading to spectrum democratization. They will support user-central communications [4] that may set novel policies and enable vendors to operate efficiently.

Efficient use and sharing of the radio spectrum are key to enabling future spectrum applications ranging from astronomy, health, atmospheric, geoscience, and environment studies to engineering systems (e.g., intelligent transportation systems). In this paper, we focus on the spectrum management and interference mitigation techniques in six representative application areas and with consideration of area-specific research challenges. The proposed research will

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considerably diversify and enrich the theoretical research on spectrum management.

Astrophysicists have been studying the properties of the Universe using frequencies across most of the electromagnetic (EM) spectrum. Different EM frequencies and frequency bands encode diverse information about the properties of the universe, and many times the same band contains information about a range of astrophysical phenomena. To properly study the received EM signals, astrophysicists must avoid all human-made sources of EM interference. Accordingly, proper EM spectrum management has an important impact on astronomical research and investigations. In the Sect. 2 of this paper, Shaul Hanany, University of Minnesota/Twin Cities, and Jacques Delabrouille, CNRS, Université de Paris and Université Paris Saclay review the key astrophysical signals in the frequency range encompassing 5G and near future 6G and higher bands.

There are vast applications of EM spectrum. Monitoring spectrum usage and the interference across these applications is critical. An example is the interference across radar and other wireless devices such as WiFi. Radar monitoring for cardiopulmonary vital signs promises to provide a valuable tool for health and safety, which will become commonplace with progress in IoT deployment. Advancement of radar-based cardiopulmonary monitoring will be facilitated by the extension of the technology to exploit signals over a greater range of the electromagnetic spectrum. Similarly, communications applications are also poised to exploit the higher frequency ranges of the spectrum. While this introduces the potential for increased interference, it also introduces the opportunity to address interference management by leveraging communication technologies to directly fulfil the role of cardiopulmonary motion sensing. In Sect. 3 of this paper, Victor Lubecke, University of Hawaii at Manoa, will provide an overview of radar technologies used in health monitoring.

Diverse radio frequency devices such as radars, lidars, and microwave imaging instruments are used to monitor components of Earth's climate system including the atmosphere, ocean, land-surface, and cryosphere. These technologies rely on different regions of the EM spectrum for atmospheric monitoring. These EM frequency bands are also used in other facets key to the health and well-being of Earth and societies. Remote sensing technologies used for weather and climate applications must have precise recognition of these frequencies because those spectral lines associated are fixed and immutable by the constituents of the climate system (e.g., we cannot change the emission properties of water vapor). Therefore, monitoring all elements of spectrum interference and designing technologies and algorithms that can reduce spectrum interference effects are imperative for socioeconomic well-being and for maintaining continuous, accurate monitoring of weather and climate. In Sect. 4 of this paper, Jason Furtado, University of Oklahoma, along with Reza Zekavat, Worcester Polytechnic Institute, will offer a detailed review of the role of EM spectrum for atmosphere monitoring.

Climate change motivates environmental monitoring that is important to the human kind. One of the key consequences of climate change is the emergence of wildfires. A key part of wildfire management and suppression success is reliable and timely access to data and information from remote sensing observations and aircraft reconnaissance for firefighters on the ground. Data resources provide context, status and a wide array of other intelligence about a wildfire that needs to be communicated around the incident command center and to and from firefighters in remote camps and on the fireline. Thus, considerable spectrum resources should be available for this application and spectrum should be properly managed to support this vital application. In the Sect. 5 of this paper, Fatemeh Afghah, Clemson University, and Nancy French, Michigan Tech Research Institute, will shed light on the details of this application.

Additionally, other geoscientists have been using EM waves for a variety of applications from analyzing volcanic activities and predicting earthquakes to exploring natural resources. Geoscientists use variety of devices that utilize EM spectrum sometimes with relatively high powers. Consideration of spectrum usage for geosciences is key for spectrum management. In the Sect. 5 this paper, Roohollah Askari, Michigan Technological University highlights the geosciences applications in Spectrum.

Section seven of this paper, will conclude that intelligent spectrum and interference management are vital components of future technologies. In addition, it highlights that a set of important technologies should be assessed in order to enable intelligent spectrum management. In addition to technology assessment, economic impacts of spectrum technologies will be important.

2 Astrophysics and Cosmology

2.1 Introduction

Astrophysicists have been studying the properties of the Universe using frequencies across most of the electromagnetic spectrum, and the need to coordinate usage of the spectrum arose soon after 1932 when Karl Jansky made the first radio observations at 20.5 MHz of emission from the Milky Way. Today this specific frequency is characterized by the International Telecommunication Union (ITU) as within the 'High Frequency' (HF) sub-band of the

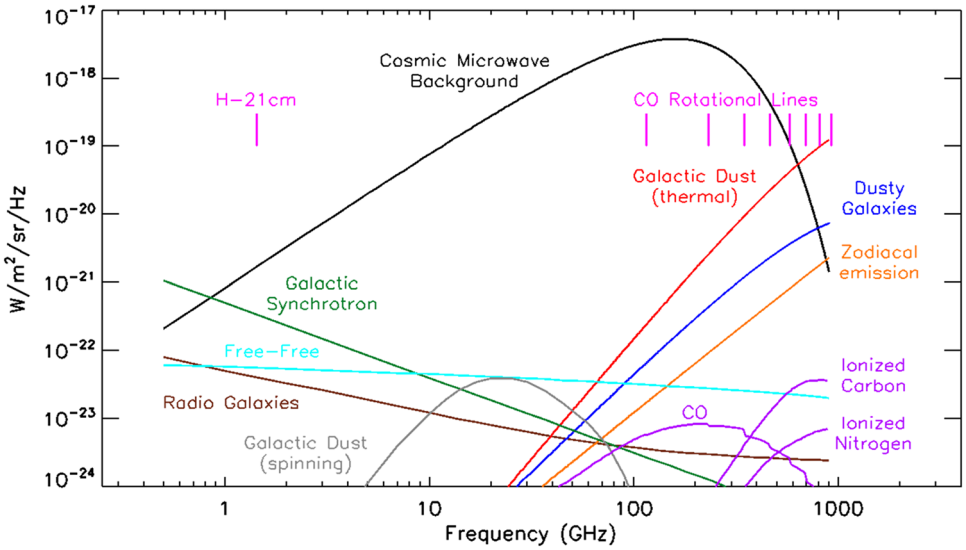


Fig. 1 Spectrum of astrophysical emissions at frequency bands close to 5G wireless bands and to future 6/7G bands. The dominant source is the cosmic microwave background. Other sources are the interstellar medium within the Milky Way, which emits radiation through synchrotron and free-free emission (labeled 'Galactic Synchrotron' and 'free-free', respectively) at low frequencies, and emission of dust grains at high frequencies that has two components, a thermal emission component at high frequency (labeled 'Galactic Dust (thermal)') and a much lower intensity component peaking near 20 GHz (labeled 'Galactic Dust (spinning)). Frequencies of some of the main atomic and molecular Milky Way emission lines are shown with small magenta vertical bars (labeled 'H-21 cm' for the 21 cm hydrogen line, and 'CO rotational lines' for transitions of the CO molecule); their vertical position is arbitrary. Similar emission processes in distant galaxies contribute a background of integrated emission from radio (labeled 'Radio Galaxies') and infrared dusty galaxies (labeled 'Dust Galaxies'), the latter also known as the cosmic infrared background. Zodiacal emission arises from the thermal emission by interplanetary particles in the solar system. The integrated emissions from extragalactic carbon monoxide (CO) rotational lines and ionized carbon and nitrogen transitions, shown in purple, are a sub-dominant part of the continuum extragalactic emission in this frequency range

radio spectrum, which in its entirety spans 12 sub-bands between 30 Hz and 300 GHz.[1] Article 5 of ITU's Radio Regulations [5] provides detailed designations of sub-bands starting at 13.36 kHz and extending up to 275 GHz for use by various applications including radio astronomy.

5G wireless systems span a frequency range from 0.45 to 52.6 GHz; 6G wireless and subsequent systems are expected to venture into higher frequencies. We review some of the most prominent astrophysical signals in this frequency range.[2] Figure 1 shows the primary sources of emission in this frequency band.

2.2 Sources of Radiation

The most intense source of intensity over much of this spectral range is the 'cosmic microwave background radiation' (CMB) a relic remnant from the Big Bang. When the Universe was somewhat younger than about 400,000 years old – that is, somewhat earlier than 0.003% of its current age of nearly 14 billion years – it was filled by a hot plasma of ionized atoms and photons scattering off free electrons. As the universe expanded and cooled the energy of the photons dropped, allowing electrons and protons to combine and form hydrogen atoms. Since the photon-hydrogen scattering cross section is vastly lower than the photon-electron one, photons effectively free stream through the Universe reaching our telescopes and conveying information about the Universe at its early age. They also carry signatures of astrophysical processes taking place throughout the Universe's evolution.

The expansion of the Universe has red-shifted the original CMB black body spectrum, characterized with an effective temperature of ~3000 K, to its present effective temperature of 2.725 K, as precisely determined by the FIRAS instrument aboard NASA's COBE mission [6]. The CMB has been a treasure trove of cosmological and astrophysical information, with measurements conducted on ground-based, balloon-borne, and three space missions, COBE, WMAP, and most recently Planck. Figure 2 shows sky emissions at several frequency bands as revealed by the Planck data [7]. Results of CMB measurements have garnered thousands of citations and four Nobel prizes, and have constrained the

[1] Other organizations such as IEEE and NATO have other designations for this spectral range.

[2] Another review giving a different perspective is provided by a publication of the National Academy of Sciences, Engineering, and Medicine [8].

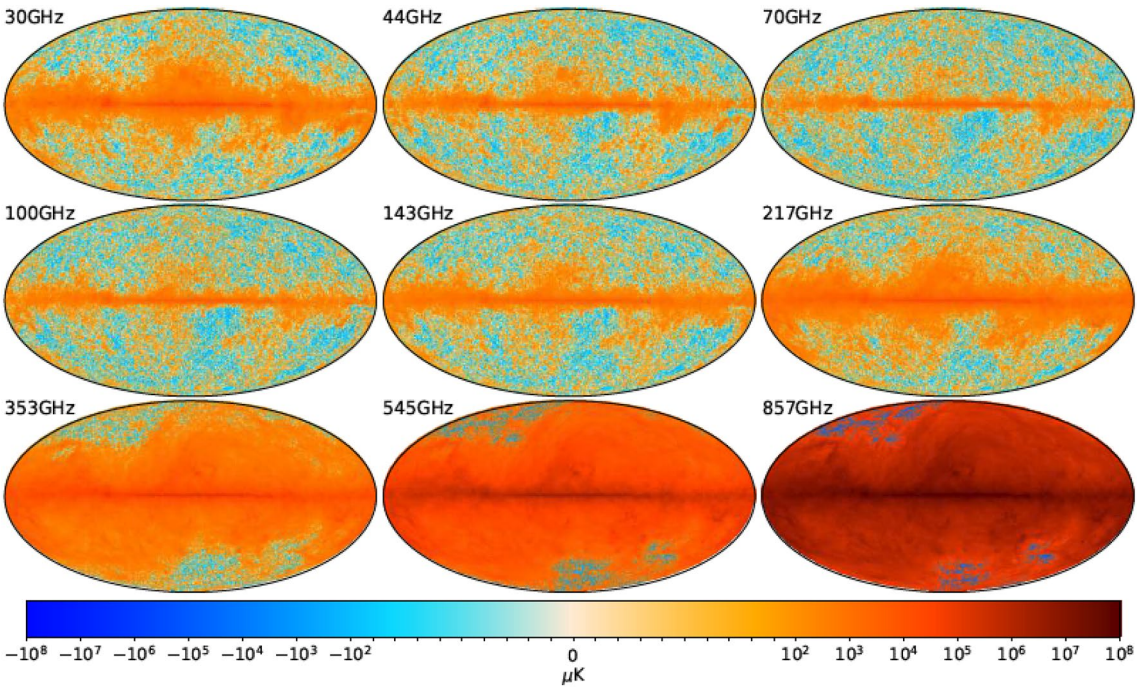


Fig. 2 Maps of continuum astrophysical emissions at frequencies between 30 and 857 GHz as measured by the Planck satellite shown in Galactic coordinates; the Milky Way is the middle horizontal strip. An isotropic uniform glow of the CMB, which is a black body with effective temperature of 2.725 k, has been removed, as well as a dipole term with amplitude of about 3 mK that is due to the motion of the solar system and the galaxy relative to the CMB frame of reference. If not removed, they would have dominated the spatial pattern. The fluctuations observed between 30 and 217 GHz are small spatial anisotropies of the CMB intensity. At low frequencies Galactic emissions are due to synchrotron, free-free, and spinning dust, and at high frequencies the signal is dominated by Galactic thermal dust; see Fig. 1. The Figure is adopted from The Planck Collaboration: Y. Akramy, et al. [7]

cosmological parameters of our Universe with an unprecedented accuracy.

At present, intense effort is directed into measurements of the polarization of the CMB. Polarization signals encode information about the physics of the Universe at fractions of a second after the Big Bang, about properties of the neutrinos, and they can further constrain the values of a range of cosmological parameters that describe the properties of our Universe as a whole.

Near 800 GHz thermal radiation from dust grains in the Milky Way become the dominant source of emission in all sky directions. The dust grains, made primarily of silicates and carbonaceous materials, have a broad distribution in size peaking around 5 microns, and their integrated emission is well described as black body with an effective temperature near 18 K multiplied by an emissivity that is power low in frequency. Astrophysicists are studying these dust grains because they are a fundamental building block in the formation of larger rocky objects such as planets, as well as an essential ingredient for star formation in the Milky Way and other galaxies.

The cosmic infrared background (CIB), which near 800 GHz is close in intensity to thermal dust, is the integrated emission from unresolved galaxies across the Universe. Like our Milky Way, many of these galaxies have dust grains and the integrated emission of these source peaks in the infra-red band of the spectrum. The integrated emission is dominated by 'star-forming' galaxies, which are galaxies that host a more vigorous star formation activity. Studies of the CIB thus are an excellent probe of the properties of such galaxies across cosmic history.

Magnetic fields with a strength of few micro-Gauss thread the entire Milky Way. Freely propagating energetic electrons spiral around these magnetic field lines, a consequence of the Lorentz force, and emit synchrotron radiation. The strength of magnetic fields and distribution of electrons' energy make this radiation peak at much lower frequencies, and at frequencies of interest the spectrum is falling steeply with increasing frequency. Scattering of less energetic free electrons by ionized atoms is another source of integrated emission, called free-free emission. Both synchrotron and free-free encode information about the distribution of matter within our galaxy, the sources of free charged particles, and the distribution and source of Galactic magnetic fields.

Some of the Galactic dust particles that give rise to the thermal emission, particularly those with nanometer dimensions,

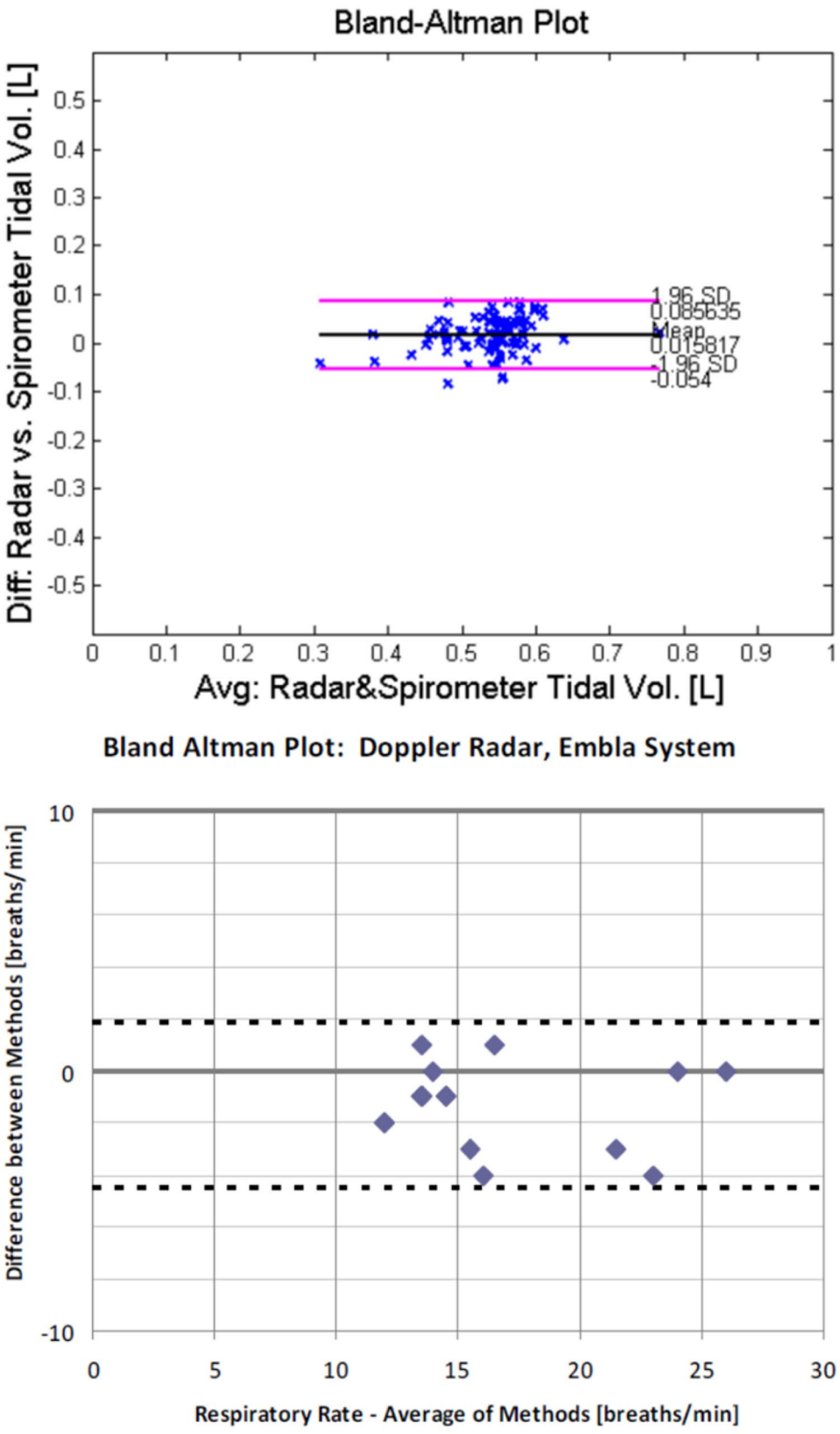


Fig. 3 Statistical analysis of radar respiration monitoring. Bland–Altman plots indicate parity of radar compared to chest strap rate monitor (left) and tidal volume spirometer (right) [18, 19]

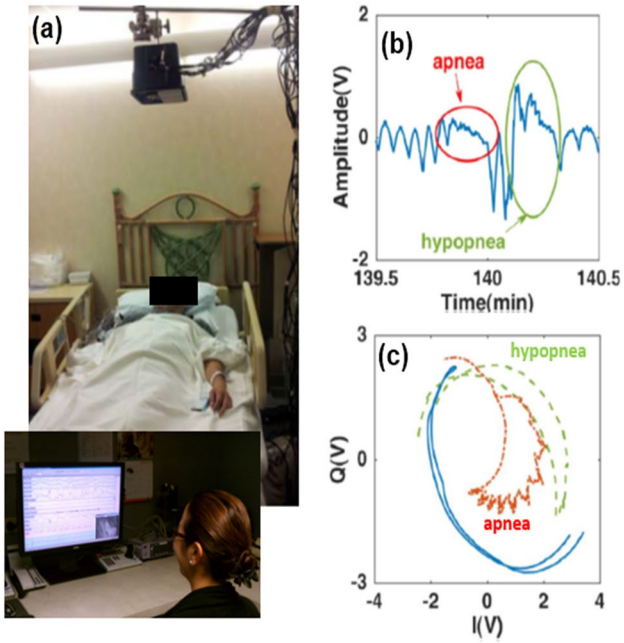


Fig. 4 Sleep apnea clinical study (**a**) and corresponding radar amplitude-time signatures for apnea and hypopnea events measured at 2.4 GHz (**b**) and I-Q trace signatures measured at 24 GHz [21]

are hypothesized to have an electron dipole moment and to spin rapidly, giving rise to an additional source of emission that peaks at few tens of GHz. If identified with high confidence and characterized with better accuracy, this emission would shed more light on the physics of dust grains.

The emission mechanisms described so far are inherently broad band. Energy transitions of neutral and ionized molecules within our Galaxy and in other galaxies give rise to a rich series of emission lines at characteristic, well known frequencies. Examples of emission lines include recombination lines of ionized hydrogen and other atoms, rotational lines of polar molecules such as carbon monoxide, and most notably the 21 cm hyperfine splitting line of neutral hydrogen, among many others; see for example [8, 9]. These emission lines are essential to the understanding of the physics and chemistry at work in denser regions of the GISM such as molecular clouds, and of the dynamics of the cold gas in galaxies. They are also essential to understanding the formation of atoms and molecules in the Milky Way as well as in distant galaxies in the Universe.

When observing extragalactic sources, the frequencies at which these lines are observable is red-shifted to a lower frequency, and the magnitude of the shift depends on the distance of the source. A number of ground-based observatories are striving to detect and map the redshifted 21 cm line because it traces the evolution of hydrogen gas across cosmic time. Because hydrogen is distributed across the entire volume of the universe, 21 cm emission occurs over very broad frequency range between tens of MHz to 1.4 GHz. Interference by existing 4G and 5G devices as well as radio and TV stations are a significant source of contaminating foreground for these experiments.

2.3 Radio Interference Challenges and Conclusions

Rich astrophysical information about the nature of the Universe is deposited across the entire 5, 6 and 7G frequency bands. Observations are conducted by multitude ground- and balloon-based observations, and occasionally by space-based

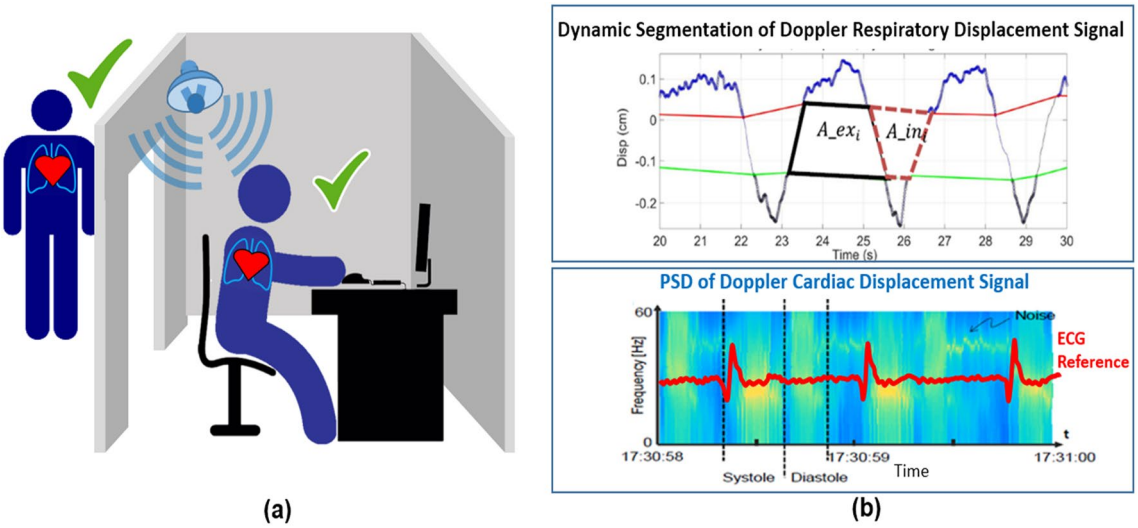


Fig. 5 Radar authentication concept and examples of respiratory dynamics pattern classifier (upper) and cardiac signal power spectral density (PSD) (lower) used for subject recognition [21–23]

missions. It is essential to understand the drivers and constraints of the many clients of the spectrum and optimize its use for the benefit of science and of other uses.

3 Remote Sensing of Cardiopulmonary Vital Signs

When wireless signals scatter off a human body, the reflected signals are modulated by body motion and thus encoded with valuable information related to physiology or activity. The collection of such data constitutes remote sensing, whether it involves the passive reflection of ambient electromagnetic signals or the use of an active interrogation signal. As with communications, various wavelengths offer unique measures and modes of operation. While current commercial applications are mostly limited to traffic and occupancy monitoring, such sensing can expand to disrupt the fields of health and security monitoring and impact society on a vast level, particularly as suitable higher frequency technology matures.

3.1 Radar Monitoring of Cardiopulmonary Activity

Continuous electromagnetic signals have shown promise for cardiopulmonary remote sensing at frequencies ranging from the ultrahigh frequency (UHF) range [10] through the terahertz (THz) range [11]. Signals at the lower end of this frequency range are commonly encountered in communications using handheld transceivers and cordless phones, and penetrate particularly well through building walls yet still provide suitable resolution for measurement of respiration or heart activity. In fact, the penetrating quality of such signals has even made such sensing possible underwater [12]. These operate on the Doppler principle and phase demodulation is used to detect body surface motion down to the millimeter level. The most advanced physiological sensing demonstrations have come in the somewhat shorter wavelength microwave spectrum. In this range physiological body motion has been measured and analyzed to quantify measures such as respiratory and heart rates, heart rate variability, pulse pressure, respiratory tidal volume (Fig. 3), gait irregularities, sleep apnea (Fig. 4), and even identity authentication (Fig. 5). While much of this work has involved active radar, there have been various passive demonstrations including the leveraging of Wi-Fi signals [13, 14]. Measurements in the millimeter and submillimeter wave spectra (THz) offer increased resolution but present greater challenges in signal to noise ratios and demodulation methods. This range has also been successfully applied for imaging in security and food screening, collision avoidance radar, and tissue diagnostics, making possible increased opportunities for leveraging in physiological monitoring applications [11].

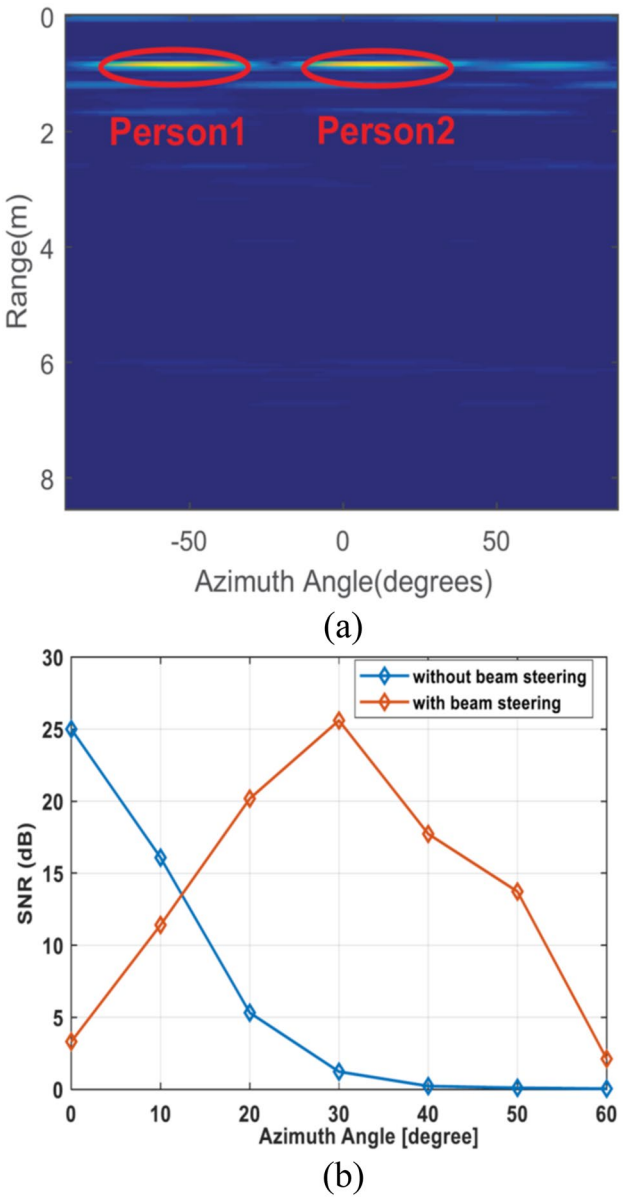


Fig. 6 Beamforming to identify multiple subjects. Isolation of two subjects (upper) and SNR comparison for millimeter-wave radar measurements [24, 25]

3.2 Applications and Challenges

Remote sensing of cardiopulmonary vital signs can be a key asset in healthcare and security applications as it offers an approach to ubiquitously monitor subjects without interference to normal activity [15–17]. Doppler radar cardiopulmonary monitoring technology is based on the sensing of body motion associated with cardiac and respiratory activity, and thus must not only address the challenge of resolving a wide range of small displacements but also that of distinguishing motion of interest from interfering motion within the monitoring field of view.

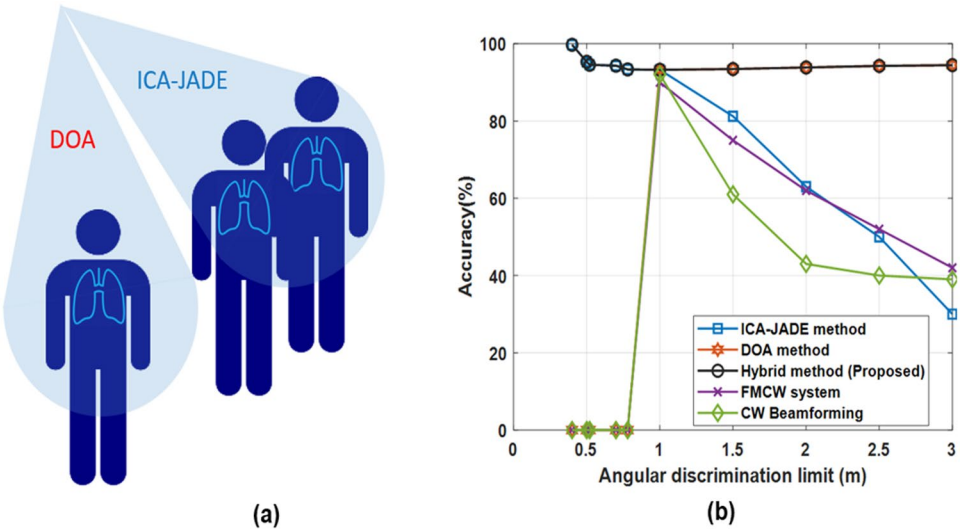


Fig. 7 Concept for hybrid-based separation of subjects (**a**) and performance illustrating the proposed method-maintained separation accuracy above 93% for separations both less than and greater than 1 m (**b**) [26]

In healthcare, microwave sensors have already demonstrated parity with industry standard contact sensors for measurement of respiratory activity including respiratory rate and tidal volume. Figure 3 (left) shows a successful Bland–Altman equivalence assessment comparing a microwave radar measurement with a conventional chest strap system [18], while Fig. 6 (right) shows parity of a similar radar system with a spirometer [19]. Microwave radar has also been used to successfully recognize the occurrence of obstructive sleep apnea (OSA) events on par with conventional polysomnography methods [20], as shown in Fig. 4.

In security applications microwave and millimeter wave technology has been applied well beyond the sensing of motion in restricted areas to the actual recognition of a subject based on cardiopulmonary activity. Figure 5a illustrates one of the features used in learning to recognize individual respiratory pattern dynamics and Fig. 5b shows recognition based on cardiac signal power spectral density (PSD) [21–23]. These vital signs monitoring demonstrations were conducted with equipment operating in the same manner as communications devices within the ISM band and thus interference could be managed with conventional communications channel management techniques. Extension to higher frequencies could offer improved resolution and pattern recognition, however an approach for interference management must also be implemented for the spectral segment of interest.

Additional complexity is introduced when multiple subjects are within the field of monitoring, as the combined motion of all subjects results in modulation of the reflected signals which must be analyzed creatively to extract signals for particular individuals. This challenge can be met through

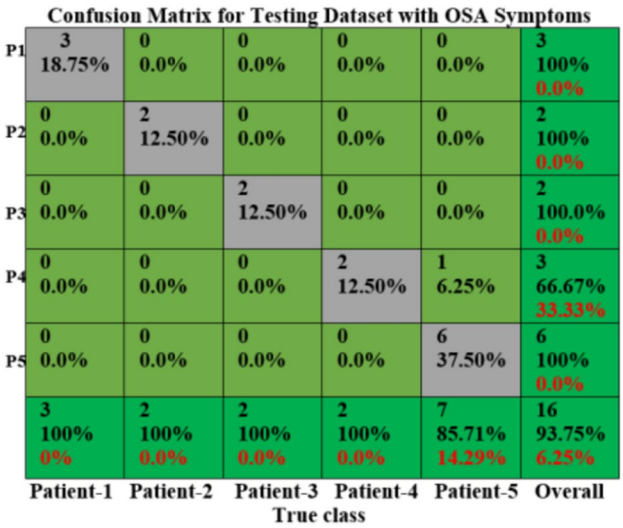


Fig. 8 Machine learning pattern recognition examples. Fast measurement of heartrate (upper) and confusion matrix for subject identification (lower) after training with known data [27, 29]

hardware and software advances. Adaptive beamforming can be applied to steer a narrow beam across the area of interest in order to reduce the problem to that of monitoring a single subject. Such an approach is made more practical when conducted at millimeter-wavelengths where the physical dimensions of antennas elements and arrays can be kept small while allowing for a narrow beam-width.

Figure 6a illustrates the separation of two well-separated human subjects using a 77-GHz FMCW radar with adaptive beamforming [24], while a comparison of signal to noise ratio (SNR) for a similar system used to measure

cardiopulmonary vital signs is shown in Fig. 6b [25], with and without beam forming. While beam steering can be applied for subjects separated by a distance equivalent to the antenna beam-width, alternative approaches are needed for more closely spaced subjects. Independent component analysis (ICA) combined with the joint approximation diagonalization of Eigen-matrices (JADE) algorithm has been used to successfully separate subjects closely positioned within the antenna beam-width [26]. This approach is illustrated in Fig. 7 along with the performance of a hybrid approach which optimally chooses between direction of arrival (DOA) beamforming and ICA/JADE separation. Millimeter-wave radar systems facilitating FMCW and beamforming are being applied to automotive collision avoidance and are thus becoming readily available for vital signs sensing, yet are also imposing a challenge for interference mitigation.

3.3 Emerging Applications

One of the latest developments in cardiopulmonary sensing involves the use of machine learning to aid in the recognition of distinct patterns of interest. Machine learning has been used in applications including the separation of heartbeat motion from respiratory motion [27], the recognition of OSA events (93–100%) [28], and recognition of an individual's identity [29], as illustrated in Fig. 8. In machine learning pattern recognition is learned from training data, thus the efficacy can be improved with the collection of multi-dimensional patterns as well as increased resolution within each pattern. Advanced biomedical imaging has been demonstrated in the terahertz spectrum [11], and may thus contribute powerfully through both mechanisms to these pattern recognition applications.

As a summary, Radar monitoring for cardiopulmonary vital signs promises to provide a valuable tool for health and security which will become commonplace with progress in IoT deployment. Advancement of radar-based cardiopulmonary monitoring will be facilitated by the extension of the technology to exploit signals over a greater range of the electromagnetic spectrum. Similarly, communications applications are also poised to expand to exploit the higher frequency ranges of the spectrum. While this introduces the potential for increased interference, it also introduces the opportunity to address interference management by leveraging communications technology to directly fulfil the role of cardiopulmonary motion sensing. Figure 9a illustrates methodology for use of channel state information (CSI) from a Wi-Fi communications system to monitor respiratory activity [13], while the extension of this approach to millimeter-wave signals is shown in Fig. 9b [14]. This approach bases sensing on the recognition of anomalies in the CSI data that normally serves to identify optimal channel selection through SNR for communications. This approach can amount effectively to a passive radar scenario, where no new, or at least no unconventional signal transmissions are introduced to spectral traffic. Ultimately the effective management of the expanding exploitation of the electromagnetic spectrum will depend upon approaches such as these to avoid the problems associated with uncoordinated competition for spectrum.

4 Instruments and Spectrum Challenges for Atmospheric Remote Sensing

Here, we first introduce an overview of the communication systems and Instruments used for atmospheric sensing and then investigate the challenges for atmospheric remote sensing.

4.1 Overview of Communications Systems and Instruments Used for Atmospheric Remote Sensing

4.1.1 Satellites

Satellites imagery and Radio Frequency (RF) systems offer near-global scale monitoring of the Earth climate. Visible and infrared satellite images provide near-real time assessment of cloud types, e.g., [30], storms, land-surface conditions (e.g., snow cover, near-surface temperatures), and wildfire monitoring. Additionally, passive radiation allows us to detect several other climate system variables, including water vapor content, 3-D temperature profiles, ocean surface temperatures, and cloud types, e.g., [31]. The frequencies at which these variables are captured are determined by the properties of Earth's atmosphere, and as such they cannot be changed or altered. Examples of key frequency bands include e.g., [32].

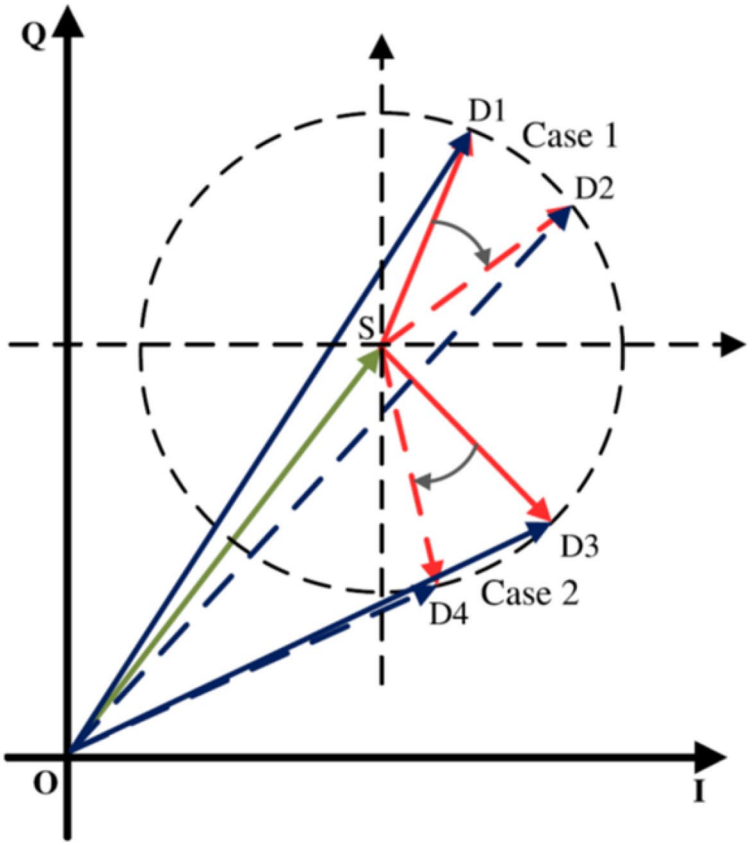
< 10 GHz: At these frequencies, the atmosphere is virtually transparent, allowing for detection of surface properties of Earth (e.g., land and ocean surface temperatures, soil moisture and temperature, sea ice).

~ 24 GHz: This frequency band is a critical band for monitoring total column water vapor estimates, important for weather and climate applications (e.g., storm formation, energy balance/the greenhouse effect).

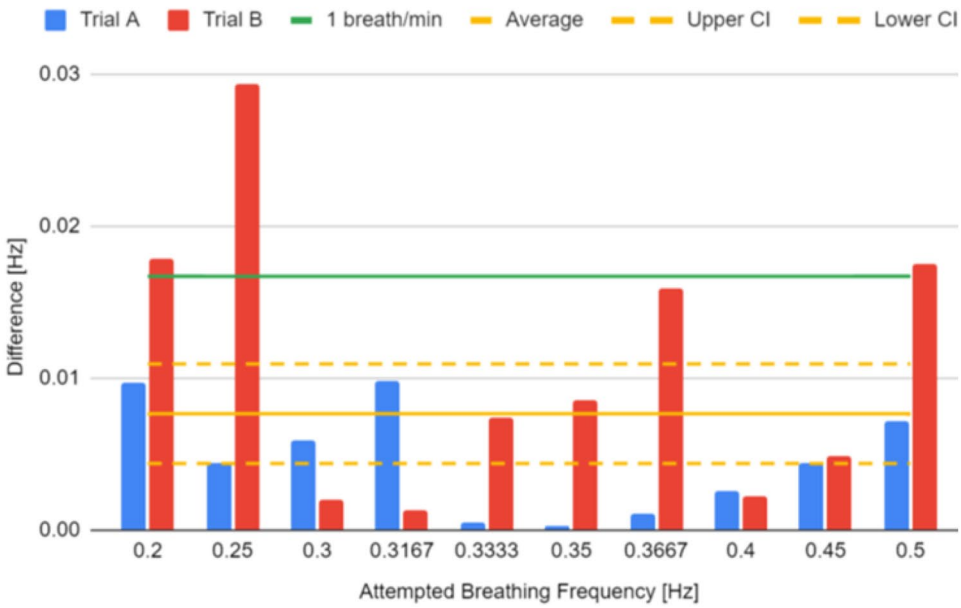
~ 31 GHz: This band is sensitive to total cloud liquid water, thus allowing detection of warm (i.e., mostly liquid) clouds.

~ 50–60 GHz: 3-D temperature profiles are obtained around this frequency band because of the strong absorption by oxygen at these frequencies.

> 100 GHz: At these higher frequencies, we look for single absorption bands for water vapor and ice in order



(a)



(b)

Fig. 9 Leveraging CSI for cardiopulmonary monitoring. IQ analysis of Wi-Fi CSI (**a**), and statistical analysis of 5G NR CSI for respiration measurement (**b**). [13, 14]

to determine different forms of precipitation and the presence of ice clouds. The ~ 183 GHz frequency band is another important band for water vapor.

4.1.2 Radar and Lidar

Surface-based radar (**Ra**dio **D**etection **a**nd **R**anging) systems are the primary tools used for detecting, monitoring, and nowcasting (i.e., very near-term forecasts) precipitation, severe weather, and clouds (see [33] for a general review). The primary bands used for precipitation detection include *S*-band (2–4 GHz), *C*-band (4–8 GHz), and *X*-band (8–12 GHz). *S*-band radars are the most popular used for large-scale weather detection by international agencies (e.g., the US National Weather Service), as this band receives almost no interference or attenuation from other atmospheric constituents. Cloud detection radars are at higher frequencies – often in the Ka (30–40 GHz) or W bands (75–100 GHz), which correspond to maximum atmospheric transmission for those phenomena. Conversely, on the other end of the spectrum, *L*-band radars (1–2 GHz) are used mainly by aircrafts for clear air turbulence detection. Natural interference for atmospheric radars comes mainly in the *X*-band, as other atmospheric constituents can emit/transmit at those frequencies. By contrast, lidar (**Li**ght **D**etection **a**nd **R**anging) systems use lasers for detection of such atmospheric science applications like 3-D Earth mapping (natural and human-made features), atmospheric aerosols and their optical properties, and even wind and temperature profiles, e.g., [34, 35]. As such, these lidars operate at very high frequencies (e.g., 20,000 GHz) but can only be used for limited distances (< 2 km) and can be severely attenuated by the presence of thick clouds or vegetation.

4.2 Challenges

Remote sensing applications for studying Earth's climate and understanding the evolution of global climate change are numerous, e.g., [36, 37]. At the fundamental level, understanding and accurately capturing energy imbalances on Earth impact scientists' estimation of *equilibrium climate sensitivity (ECS)* – i.e., the total heating which Earth will experience because of increased greenhouse gas forcing once the system reaches equilibrium. Current estimates of ECS range widely from our climate models – from 1.5 to 4.5 °C for a doubling of CO_2 [38]. Therefore, we currently have very large uncertainties in our global climate projections of future temperature and circulation patterns. Ground-based and space-based instruments monitor and record several 3-D climate variables needed for calibrating climate model simulations of present and future climate states.

One key variable for monitoring atmosphere is its water vapor content, which impacts the hydrological cycle and also Earth's radiative balance, as water vapor is a powerful greenhouse gas. As mentioned previously, the ~ 24 GHz channel is an important one for monitoring water vapor (water vapor also emits at higher frequencies, e.g., ~ 183 GHz). However, this frequency channel is currently being considered as part of the worldwide 5G wireless network deployment. As such, transmission of instruments with this frequency will interfere with satellite measurements of water vapor content in Earth's atmosphere, producing erroneous results for our weather and climate models [39].

Related to water vapor content, continuous active monitoring of clouds and different cloud types is a very important factor for climate change work. Cloud radiative feedbacks are one of the largest unknown responses in the climate system, e.g., [40, 41]. Current generation satellite and lidar retrievals use numerical models and machine learning algorithms based on limited (spatial and temporal) data to distinguish several cloud properties, including liquid water content, thickness, cloud top pressure, and cloud composition, e.g. [30, 42, 43]. Moreover, in order to fully capture accurate 3-D characteristics of clouds in the climate system, we must rely on several sensors and instruments as just a single instrument cannot distinguish the multiple properties needed.

Area of improvement for cloud observing and thus deriving better estimates of ECS center around understanding and quantifying the changing cloud types in response to global climate change. The percentage of high altitude (e.g., cirrus) versus low altitude (e.g., stratus/stratocumulus) cloud cover on Earth has enormous impacts for the Earth radiative balance and can create feedbacks with the land surface and thus with the climate system. As global climate change alters surface temperatures and atmospheric circulation patterns, cloud types will also change. Additionally, changing cloud types and properties also alter precipitation efficiency and formation, thus, impacting the global hydrological water cycle. Atmospheric scientists' ability to monitor these clouds and related precipitation and humidity profiles require clear signals from the ~ 24 GHz, 31 GHz, 50–60 GHz, and ~ 183 GHz channels.

Aerosol-cloud interactions are another major component of monitoring for climate change. Detecting atmospheric aerosol types and concentrations globally inform scientists about several aspects of the climate system, including atmospheric albedo. Aerosols are also of huge concern for public health, especially anthropogenic sources of aerosols from industry and agriculture, e.g., [37]. Detection of aerosols occurs primarily via light scattering. Unfortunately, a single remote sensing instrument for aerosols can have trouble distinguishing light scattering from aerosols versus clouds or even land reflectance. Moreover, clouds and other atmospheric constituents complicate aerosol detection algorithms (which are often empirically derived). The current solution

is to employ multiple instruments designed for different constituent detection (e.g., polarimeters, radiometers) and then working to differentiate "noise" (i.e., non-aerosol) from the "signal" (i.e., the aerosols themselves). Bridges forward would involve not only improvements to the remote sensing instruments and spectral detection by the instruments but also combining space-derived measurements with extensive, high resolution surface-based observational networks of aerosols. Doing so would allow scientists to discern the importance of local and regional landscapes (e.g., rural vs. urban). The volumes of data and the need for high-frequency transmission of this data for retrieval algorithm and near-real time monitoring are other significant improvements needed.

For weather applications, challenges arise in two main arenas. One is the continued expansion of the communications into lower frequencies, particularly encroachment into *S*-band frequencies. As these frequency bands are crucial for detection of storms and other precipitation, any degradation or interferences at these frequencies will hinder effective weather monitoring and public weather warnings. Second, our ability to monitor weather systems rely heavily on fixed-radar systems. These systems are generally located near major population centers but can suffer beam blockage and/or false echoes due to topography, urban settings, or other human structures (e.g., windfarms). Additionally, our ability to monitor storms beyond the radial sweep of a single radar is problematic, particularly for storms in the ocean. The ability to use other devices to fill in the gaps and reduce radar "noise" would be extremely useful for advancing both near-term forecasts of weather hazards and long-term monitoring of such events for modeling studies.

As a summary, diverse radio frequency devices such as radars, lidars, and various satellite products (e.g., microwave imaging) are used to monitor the various components of the Earth physical climate system (e.g., the atmosphere, ocean, land-surface, cryosphere). These technologies rely on different regions of the electromagnetic spectrum for atmospheric monitoring that are also used in other facets key to the health and well-being of Earth and societies. Precise reading of these technologies is important because the spectral lines associated with these technologies are fixed and immutable by the constituents themselves (e.g., we cannot change the emission properties of water vapor). Therefore, monitoring all elements of spectrum interference and designing technologies and algorithms that can reduce spectrum interference effects are imperative for socioeconomic well-being and for maintaining continuous, accurate monitoring of weather and climate.

5 Spectrum Challenges for Real-Time Wildfire Monitoring

A key part of wildfire management and suppression success is reliable and timely access to data and information from remote sensing observations and aircraft reconnaissance for firefighters on the ground. Incident commanders are reliant on data for situational awareness, to plan daily operations, and to run predictive models of fire behavior and smoke. Data resources provide context, status and a wide array of other intelligence about a wildfire that needs to be communicated around the incident command center and to and from firefighters in remote camps and on the fireline. Current data delivery capabilities for operational information sharing cannot transmit some very large data resources that have potential value for accurate decision-making. Images are downgraded or interpreted into point and line graphics to make them small enough for efficient transfer. This means that experts are not always able to access important information for decision-making, and they rely on derived rather than raw information that may convey inaccurate or incomplete information.

Because of rapid advances in data collection, remote sensing, and geospatial data analysis, requirements of a data sharing system for disaster management, including wildland fire, have not been fully explored or defined. In fact, data sharing limitations of current systems are not well articulated, because technologies to provide large data sets in a timely manner to front-line decision-makers are not commonly available. A new effort to improve access to critical datasets in disconnected situations, such as a wildfire incident command post and distributed firefighters, is the development of the wildfire data logistics network (WildfireDLN [58]). The functions of the WildfireDLN storage nodes can make use of whatever underlying communication mechanism is available. Collections of such operations that may comprise complex communication functions are managed by higher level services, each of which has its own assumptions and requirements which can use a variety of different mechanisms to implement a complex function. The common layer of shared buffer services that define the lowest layer of the WildfireDLN enables a wide variety of policies and mechanisms for isolated, disrupted, distributed and heterogeneous communication and data management services, therefore offering resiliency in the context of disconnected network operations.

5.1 Drone-Based Fire Monitoring

Wildfires are one of the costliest and deadliest natural disasters in the US and other parts of the world. The southwestern U.S. is one of the most fire-prone regions of the world, with

approximately 2000 lightning-caused wildfires annually on Federal lands [44]. Wildland fires endanger human lives, damage the infrastructure, forest lands and other natural resources with negative consequences on wildlife, water quality, and other ecosystem services [45]. The frequency of western U.S. wildfires has increased by 400% since 1970. The rapidly increasing risk of fire is mostly due to recent widespread extreme drought conditions, and climate warming which calls for new technologies for early detection and management of wildfires [46]. The current wildfire detection techniques cannot provide an agile and accurate observation of wildfire, in particular in remote and hard-to-reach areas. For instance, the satellite images which are commonly used in fire detection due to their global coverage, are costly and suffer from considerable delay and often low resolutions. Wireless sensor networks can offer an affordable solution for fire detection but they often cover a limited coverage area and a short lifetime.

Unmanned aerial vehicles (UAVs) have been recently utilized in disaster management operations such as fire detection and management, search-and-rescue and evacuation operations to collect data/imagery for a ground command station or a rescue team in close proximity [47–52]. The UAVs can offer unique features in such operations including tracking the fire front line, fast mapping and of wide areas even in remote and hard to reach areas, emergency deliveries, real-time video streaming of the impacted areas, search-and-rescue and many more actuation abilities expected in new generations of drones. An important advantage of drone-based fire detection and management is the fact that the drone can operate in an autonomous or semi-autonomous mode, hence it can eliminate the need for firefighters and first responders to be in a close proximity of the fire zone.

5.2 Challenges

One of the main challenges related to the operation of UAVs for high-resolution imaging and video streaming in remote areas is communication [53]. This issue is even more critical during disasters when the communication infrastructure may be damaged. The communication of UAVs is divided into two categories of control and non-payload communication (CNPC) that refers to communications among the UAVs or between the UAVs and the ground station for high-propriety delay-intolerant control, coordination, or flight operation information and the payload communication to transfer sensed information to the ground station that requires high data rate transmission [54]. Noting the importance of the CNPC in the operations of an individual or a group of UAVs, it requires reliable communication on a dedicated radio spectrum. Such dedicated spectrum for CNPC has been allocated to the medium and large UAVs by the Radio Technical Commission for Aeronautics (RTCA), however, there is no current policy developed for small UAVs.

Several efforts led by federal agencies and international communities currently focus on investigating proper communication technologies for CNPC of UAVs [55, 56]. The available candidates include using the cellular communications (e.g., LTE) and wireless local areas networks (e.g., WiFi) that may suffer from a congested network in urban areas or lack of services in rural areas. Other recent candidates are (i) ultra-reliable low latency communication (URLLC) in 5G that is designed for latency sensitive applications such as autonomous driving, ii) satellite communications in very remote areas that suffer from long latency, and the need for directional antennas, and (iii) long range communication (LoRa) that is designed for low data rate transmission over long distances with low power consumption [57].

The focus of the majority of current research work is to develop communication protocols for UAVs' CNPC communication, however, the success of UAV networks in critical missions (e.g., real-time monitoring of disaster-impacted areas) relies on reliable payload communication. In these missions, the pre-allocated spectrum of UAVs may not be sufficient to transmit high-throughput imagery, hence on-demand access to additional spectrum is required. This need for additional spectrum calls for novel dynamic spectrum sharing technologies.

5.3 Related Works

A recent nationwide initiative called 'FirstNet' aims at providing prioritized communications for first responders over a reliable LTE network in partnership with AT&T, where a wireless broadband network dedicated to public safety will be established. While this is an invaluable effort, it could be years of delay waiting for this broadband communication to be available in rural areas. Even when such a network is available, if the LTE towers were out of order, the alternative communication using radio access networks (RANs) in mobile vehicles may still take a while to be set up in the remote regions or areas impacted by disasters. Therefore, in UAV-assisted disaster monitoring, the UAVs should be equipped with a flexible communication system that could efficiently and rapidly utilize all possible network resources available in the impacted region.

MmWave communication has been discussed as an option for payload communications of UAVs as a part of 5G, but the technology is not widely available yet. Moreover, the communication is impacted by high propagation path loss, thereby, it requires the UAVs to be equipped with high directional antennas to avoid blockage zones and maintain a LOS communication. The few existing works related to spectrum sharing with drones mainly focused on the coexistence of

UAV networks with cellular networks and adopted common notions of spectrum sharing such as interweave method to let the UAVs opportunistically access the spectrum holes of other communication systems, or the underlay method to allow the UAVs to utilize the spectrum of other systems while maintaining a low interference level [59–62]. The objective of these methods is to guarantee an expected quality of service (QoS) for the incumbents noting the imperfection in spectrum sensing or the synchronization errors. The spectrum sensing method is not an ideal option to provide additional spectrum for UAV networks noting the considerable energy consumption involved in searching a wide range of frequencies to detect the spectrum holes. Due to the chance of unexpected return of primary users, it cannot assure the required session length. More importantly, these spectrum holes are often sparse and appear on different frequencies, therefore it cannot offer continuous communication for the UAV system or require frequent change of the operating frequency. The spectrum sharing trend based on databases control (e.g. TV White Space) also require the UAVs to have direct access to geolocation databases or be enabled through authorized master users. This method cannot be a practical model for spectrum sharing with autonomous UAVs in disaster management missions, because this technique only provides spectrum access in limited zones.

5.4 Cooperative Spectrum Leasing in UAV Networks

One key drawback of these conventional spectrum sharing methods is that the spectrum owners are oblivious to the presence of the devices seeking for spectrum, but a dynamic and efficient practical spectrum sharing model cannot be implemented unless different users including the spectrum owners and the ones looking for spectrum interactively cooperate with one another [63–67]. Moreover, current spectrum sharing techniques are biased on a traditional mindset that only considers the rights and benefits of spectrum owners (primary networks), however, as new generation of communication technologies and services evolve over time, there is a need for novel spectrum sharing techniques that can account for the benefits/requirements of both primary and secondary networks. This fact is of particular importance in disaster monitoring and public safety applications where the secondary networks (i.e., the UAVs) carry high-priority information.

Cooperative spectrum sharing technologies hold great promise for dynamic spectrum access in disaster situations. The potential benefits of this model are to use the infrastructure or resources of other communication networks to extend the connectivity, lifetime, or data transmission rate of networks with critical missions. In cooperative spectrum sharing mechanism, the primary network allow the UAVs to access their spectrum for a certain time in exchange for cooperative relaying services or adding intentional jamming to enhance the physical layer secrecy of the primary users [63, 67]. For instance, during disaster situations, the cellular users may not have access to the network due to the damage to the communication infrastructure in their region, or they may need to utilize a high transmission power to access other towers (beyond their normal range), or the link between the devices in D2D communication may be blocked due to strong shadowing. These facts encourage them to participate in spectrum sharing with the UAVs to obtain the chance of packet transmission with the assistance of flying UAV relays. In this model, both the spectrum owners and the UAVs can take into account their current QoS requirements, the network and environment conditions as well as the type of other communication devices in the environment in order to select the best spectrum sharing strategies.

5.5 Conclusions

Since there are still several open issues related to both data access and sharing as well as flight policy, operation, coverage, connectivity and communications of the UAVs, the problem of spectrum management in UAV networks, especially those used for data collection and sharing, has been barely investigated so far. However, the spectrum scarcity will be a serious challenge in UAV networks given the increasing number of UAVs and the requirements of advanced wireless services. Developing spectrum sharing strategies for UAV communication requires extensive experimental studies to provide more insights on channel models between the UAVs and ground stations and the UAV-UAV channels, as well as the interference caused by UAVs on terrestrial networks. Common spectrum sharing models such as underlay seem reasonable for spectrum sharing between the terrestrial networks (e.g. cellular networks) and UAV-to-UAV communications when the UAVs are flying at high altitudes. However, new spectrum sharing models such as cooperative spectrum leasing where the primary network deliberately share a portion of its spectrum access with the UAV network would offer a promising solution to avoid undesired interference while allowing the primary network to benefit from UAV services such as cooperative relaying.

6 Geosciences Applications

6.1 Overview

Electromagnetic (EM) waves [68] have been widely used by geoscientists for a variety of applications from analyzing volcanic activities [69] and predicting earthquakes [70] to exploring natural resources [71]. Depending on the signal frequency, EM techniques can be divided into two major groups of very low frequency (VLF) EM induction [68] and

high frequency (radar) reflection methods [72]. The former incorporates a primary VLF EM (1–29 kHz) to induce an Eddy current into the ground, from which a secondary magnetic field is generated. By analyzing secondary magnetic field, we can estimate the conductivity of subsurface material [68]. Thus, if the target of study has a different conductivity than that of the surrounding media, it can be studied via VLF-based techniques [68]. On the other hand, in the high-frequency reflection-based method, which is termed as Ground Penetrating Radar (GPR), EM signals in the range of the radar frequency (mega to gigahertz) are sent into the ground. If two geological interfaces have different permittivities (ε), a fraction of the EM energy is reflected back to the surface, from which a detailed image of subsurface can be obtained [72].

6.2 VLF EM Induction

The VLF-based induction methods can be divided into two passive and active source subcategories. In passive VLF induction, EM signals generated by natural phenomena or radio waves from naval communications are utilized, whereas in active VLF induction methods, EM signals initiated from a controllable transmitter are used.

Magnetotelluric (MT) is a passive ultralow frequency EM method, stemming from natural phenomena [73]. One source of MT is currents within the ionized layers of the atmosphere that are generated from solar activities [73]. Such currents can induce EM waves with frequencies as low as 10–3 Hz to 10 Hz [73]. In addition, MT can be initiated from electric discharges of distant thunderstorms [74] with frequencies ranging from 10 Hz to 10 kHz, also known as Audio Frequency Magnetotelluric (AFMAG). MT is suitable to study deep structures (greater than 1 km, [75]), where there is a high contrast between electrical conductivities of two subsurface structures (e.g., an oil saturated layer over a brine aquifer [76]). MT has been widely used to investigate various geological features such as silicate melts in the Earth's mantle and crust [77], tectonic activities [78], and orogenic processes [79]. Many reports have also indicated MT fluctuations before earthquakes [80, 81], and therefore, many studies have focused on characterizing MT signals for short-term earthquake predictions, e.g., [70]. Geo-exploration applications of MT include hydrocarbon reservoirs [71], geothermal resources [82], ore mines [83], CO2 sequestration [84], and nuclear waste monitoring [85].

Another source of passive EM is VLF radio signals (15 kHz to 29 kHz) used in naval communications [86]. Due to their large strength and low attenuation, passive VLF EM signals are generally detectable around the globe. Compared to MT, VLF EM has a shallower depth of penetration and is suitable to study shallower geological formations such as studying near surface faults [87] and fractures [88], identifying hydrocarbon contaminated soils [89], exploring mineral resources [90], monitoring volcanic processes [69], and investigating aquifers [91]. In addition, similar to MT, passive VLF EM signals also have shown fluctuations before earthquakes, and thus can be used as an earthquake precursor [92].

Active induction methods employ a couple of coils one serving as a transmitter and the other as a receiver. to generate and record VLF signals [68]. The distance between the transmitter and receiver depends on the investigation depth as for deeper targets, a larger distance is needed [68]. In addition to controllability and repeatability of sources, the data acquisition of active surveys is fast as the transmitter and receiver can be carried by an aircraft, known as airborne EM [93]. Given the flexibility of source and receive design, active induction methods have found a great range of applications such as soil characterization (e.g., assessing salt and clay level) for agriculture (14–15 kHz, [94]), soil moisture estimation for forestry, agriculture, and ecosystem investigation (8–10 Hz [95]), underground water for hydrology, soil contamination assessment in environmental studies [96] and exploration of natural resources (~ 0.4–6.4 kHz [97]).

6.3 Ground Penetrating Radar

As mentioned earlier, a group of methodologies, coined as the general term of ground penetration radar (GPR), relies on a fraction of EM energy that is reflected back to the surface from geological interfaces. GPR operates within the range of UHF/VHF frequencies of the radio spectrum [72]. The choice of GPR frequency highly depends on the depth of the geological target. For instance, for pavement studies where the asphalt layer has a thickness of about a few inches, GPR signals with a central frequency of 1–2 GHz are used [98], whereas for a target at the depth of 100 m, low-frequency GPR signals (e.g., 270 MHz [99]) should be incorporated. Compared to the induction-based methods, GPR provides a much higher resolution, and thus, is robust for near surface studies. Application of GPR technique include but not limited to estimating soil moisture [100], studying archeological sites [101], detecting near sinkholes [102] and buried wastes [103], evaluating leakage of buried pipelines [104] and characterizing soil in forests [105].

6.4 Challenges: Noise and Signal Interference

Noise and signal interference have been an everlasting problem in the EM methods that significantly spoil their performance. Based on their origin, EM noises are divided into two major categories of natural and cultural sources [106]. Natural noises mostly stem from natural atmospheric lightning discharges that are called radio atmospheric signals and/or sferics and have a broad frequency spectrum from 0

to 100 kHz [107]. Sferics are ubiquitous in EM geophysical data due to their frequent occurrences (100 per second worldwide [106]). Cultural noises originate from VLF and radio transmitters around the globe and machinery (for example pumps, generators, vehicles) [108–110]. In addition, metal tanks, unpowered metallic fences and pipelines and power plant facilities pipelines in the vicinity of the soundings are another major contributor to the cultural noises [111, 112]. Due to the continuous developments of residential areas, it is expected that cultural noises and spectrum interferences become a major challenge of the EM methods in geoscience and environmental studies [112].

6.5 Conclusions on Geoscience Applications

Due to the continuous developments of residential areas, it is expected that cultural noises and spectrum interferences become a major challenge of the EM methods in geoscience and environmental studies. Given the fact that the spectrum overlaps and interferences of cultural noises with EM signals, removal of those noises is not possible based on the Fourier based signals. Developing new methods based on matching learning or deep learning can address the challenge of spectrum interferences.

7 Conclusions

In order to address diverse and emerging applications of spectrum, new paradigms in intelligent spectrum management and regulations should be investigated. This paradigms need fundamental research in interference science and technology. Researchers should tackle the problem of overall resource – spectrum, computing, energy, and storage – sharing that is key to network function virtualization (NFV) and network slicing [113–115]. Doing so demands a multi-disciplinary research effort on new paradigms in intelligent spectrum management and regulation [116, 117]. The National Science and Technology Council's (NSTC) Wireless Spectrum R&D interagency working group (WSRD) summarizes the problems as [118]: (1) spectrum flexibility and agility; (2) near real-time spectrum awareness, and (3) spectrum efficiency via secure autonomous spectrum decision making. Diverse research areas that need to be advances include investigation of new algorithms for optimizing spectrum sharing [119, 120], and network virtualization via concepts such as Intelligent Radios (IRs). IRs are Ultra-Multi-Band Radio (UMBR) that enable devices to measure interference and use information collected in real-time from a large number of resources, e.g., mobiles, sensors, and use high speed computing to save and analyze data. Machine learning and data sciences are key elements of IRs. Implementation if IRs would require hardware and software design components. We anticipate that many researchers will be involved in designing radios and networks that enable spectrum management. Educating the workforce to support spectrum management technologies would be critical to communication industries.

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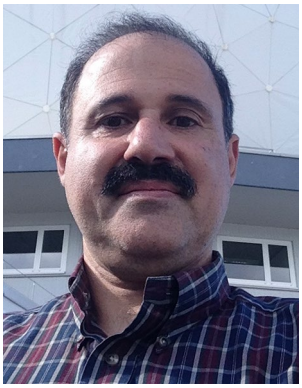

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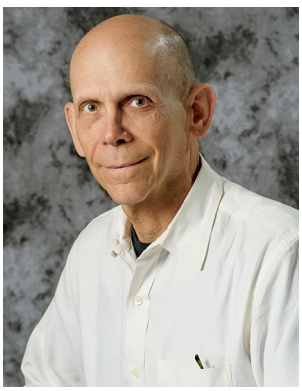

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