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# RF Computing: A New Realm of IoT Research

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**Abstract** Current Internet of Things (IoT) systems encounter substantial challenges in realizing ubiquitous sensing and connectivity, characterized by constrained sensing coverage, prohibitive deployment costs, and energy inefficiencies inherent in conventional digital-centric architectures. This paper presents RF Computing, an innovative paradigm that exploits radio frequency (RF) signals to simultaneously serve as information carriers and computational operands. By enabling direct information processing through RF signal manipulation in the RF domain, RF Computing effectively bypasses the limitations of traditional digital systems, delivering exceptional energy efficiency and superior performance characteristics. We provide a systematic definition of RF Computing, classify its operational modalities, and showcase representative applications that highlight its transformative potential. The existing research landscape is organized into three principal categories: information injection, transformation, and augmentation. Furthermore, we delineate critical open challenges, including the development of unified theoretical models, RF resource management strategies, analog-digital co-design methodologies, and programming frameworks for RF Computing systems. Finally, we propose promising directions to propel this emerging field forward.

**Keywords** radio frequency (RF), analog computing, Internet of Things (IoT), sensing

## 1 Introduction

Internet of Things (IoT), as a key technology that bridges the cyber and the physical space[1, 2], has enabled remarkable research progress in the past decades. With continuous advancements in sensing and communication technologies, IoT applications have been spread across various areas, including but not limited to healthcare[3–5], localization[6–8], and transportation[9–11].

The state of the arts in IoT, however, still falls significantly short of achieving ubiquitous sensing and connectivity. This is primarily manifested in three key aspects.

1) *Limited Sensing Capabilities and Physical Space Coverage*. Traditional sensing approaches remain constrained by the "discrete node-based coverage" model, leading to persistent challenges such as discontinuous data acquisition, incomplete coverage, and restricted spatial scope in capturing physical space information.

2) *High Deployment and Maintenance Costs*. The expense associated with the IoT technology often outweighs its potential benefits, making it less economically viable for widespread adoption in many applications.

3) *Inherent Energy Consumption Limitations*. IoT devices, predominantly based on digital signal processing, face a fundamental lower limit in energy efficiency. Efforts to reduce power consumption inevitably compromise performance, creating a direct conflict with the increasing demands for high-performance capabilities in future IoT applications.

We aim to identify the root causes behind the aforementioned dilemma. From a system architecture perspective, we observe that current IoT systems have

Cover Article

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long adhered to the design principles of general-purpose computing systems. Having followed the path of digital computing for nearly 80 years, we have grown accustomed to processing and transmitting various forms of data in the digital domain, using digital methods to understand and solve all problems. However, this also entails inevitable overhead, costs, and performance compromises[12]①.

Let us consider a basic IoT sensory data acquisition scenario. The standard workflow unfolds in the following three stages. First, a sensor detects certain information from the physical world, which is initially represented as an analog signal. This signal must first be digitized for local storage and computational processing. Next, the communication module on the sensor converts the digitized information back into an analog signal, modulates it according to specific communication and networking protocol standards, and transmits it. Finally, the receiving end captures the analog signal, demodulates and converts it back into a digital signal following the communication protocol, and then passes it to the upper layers of the network protocol stack for further processing. This sensing-transmission-computation decoupled approach inevitably leads to information loss during intermediate processing, often accompanied by excessive device costs, design complexity, and energy overhead, as is the pervasive reality of IoT.

Recent advances across multiple disciplines suggest a promising approach to addressing these challenges. Physicists have demonstrated that even simple physical systems can solve complex problems previously believed to require sophisticated computational algorithms[13]. Meanwhile, material scientists have engineered advanced materials capable of performing computations[14–17] or enabling novel sensing and communication applications[3, 18–25]. In electronics, researchers have developed highly efficient, low-power circuits and systems for RF (radio frequency) signal processing[26–31]. Antenna engineering has seen breakthroughs in structural designs that optimize RF signal manipulation, enhancing both efficiency and reliability in signal processing[7, 9, 26, 32]. Additionally, human–cyber–physical computing and neuromorphic computing systems have emerged to perform sensing and communication based on analog information, which mitigates digitization losses and reduces system complexity[33–36].

From the above research progress, we can discern a common trend: performing computations in the analog domain is an effective approach. Although it may involve a compromise in precision and speed, it often enables the resolution of problems— at much better efficiency and significantly lower cost and energy overhead— that traditional computing systems can only tackle at a much higher expense.

Based on the above understanding, we propose RF Computing, a new paradigm that uses RF signals as both information carriers and operands, so that information processing and transformation are achieved by manipulating these signals directly in the RF space. The examples in Fig.1 shows that typical computational functions can be realized with RF Computing based implementations. A combiner can work as

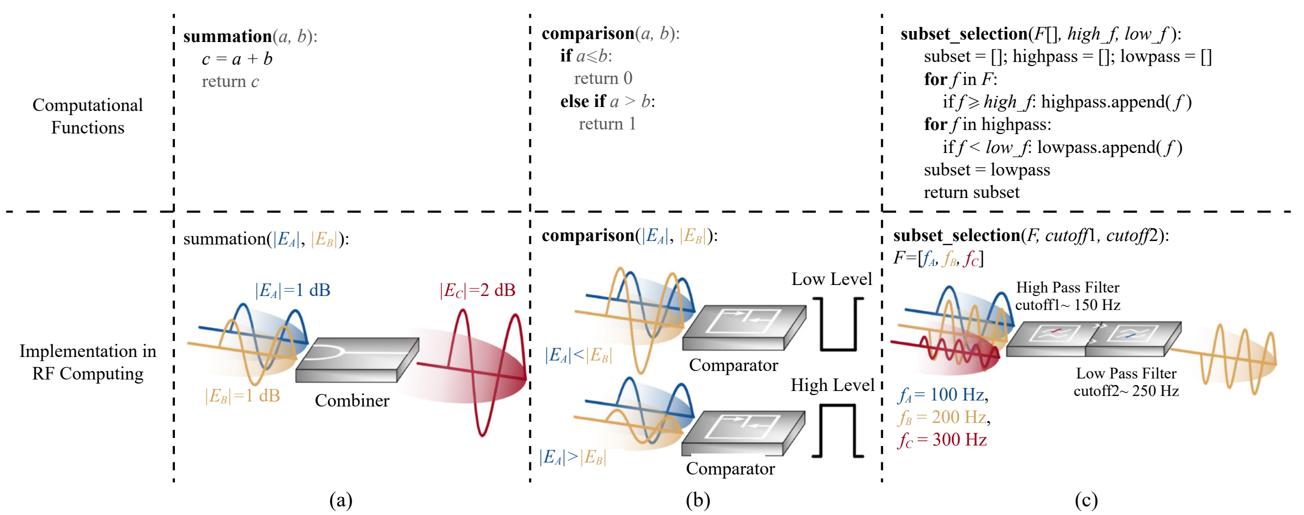


Fig.1. Typical examples of computational functions that RF Computing can realize. (a) Summation. (b) Comparison. (c) Subset selection.

①Kelly P H. "Turing Tariff" Reduction: Architectures, compilers and languages to break the universality barrier, 2020. https://www.doc.ic.ac.uk/~phjk/Presentations/2020-06-24-DoCLunch-PaulKelly-TuringTaxV04.pdf, July 2025.

an addition function by combining the two input signals. A comparator can perform a branching function. Cascaded high and low pass filters can execute the function of subset selection. Moreover, by delicately integrating these functions and corresponding RF devices within an RF Computing system, more advanced algorithms can be achieved, such as search, optimization, and classification.

The concept of RF Computing is built upon a collective foundation of decade-long research advancements across various aspects of the IoT field, such as RF-based wireless sensing[3, 4, 8, 20, 37–39], backscatter[28–30, 40–44], and cross-technology communication (CTC)[45–50, 51]. These research efforts have progressively revealed the dual potential of RF signals as both information carriers and computational operands, while simultaneously advancing the RF signal processing capabilities of IoT edge devices.

RF Computing aims to adopt a hybrid digital-analog computational approach, achieving a unification of high performance and low overhead, thereby advancing IoT systems toward the goal of ubiquitous sensing and connectivity. There are many open problems in this emerging research area. Thus, in the rest of this paper, we first present the basic definitions and concepts of RF Computing in Section 2. Section 3 introduces the status quo of RF Computing. In Section 4, we discuss the potential research space. Section 5 concludes this paper.

## 2 RF Computing: Definition and Concepts

Since RF Computing uses RF signals as the information carrier and operand, we start with presenting the basic properties of RF signals. Following a formal definition of RF Computing, we illustrate how information can be carried and processed with RF Computing operations.

### 2.1 Definition

As a kind of electromagnetic (EM) wave, an RF signal has several different domains to carry information. Specifically, according to Maxwell's equations[52], the simplest RF signal (i.e., monochromatic plane EM wave) can be formulated by

$$\overrightarrow{\boldsymbol{E}}(r,t) = E_0 \cos(\overrightarrow{\boldsymbol{k}}\, r - \omega t + \phi_0)\overrightarrow{\boldsymbol{e}},$$

where $E_0$ is the amplitude, $\overrightarrow{\boldsymbol{k}}$ is the wave vector indicating the propagation direction of the signal, $\omega$ is the angular frequency which is proportional to the frequency $f$ (e.g., $\omega = 2\pi f$), $\phi_0$ is the initial phase, and $\overrightarrow{\boldsymbol{e}}$ is the unit vector representing the polarization of the signal. Fig.2 illustrates the different five domains of an EM wave in the monochromatic plane.

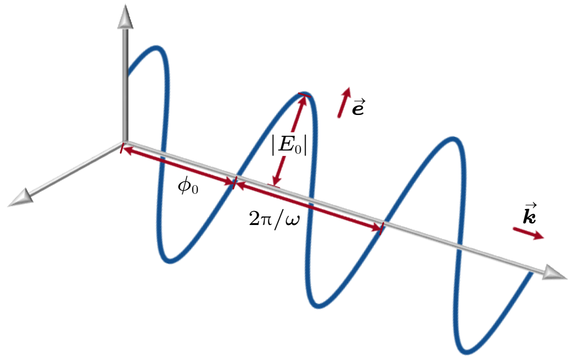


Fig.2. Different domains of the monochromatic plane EM wave.

Each of these five domains can convey distinct information, a fundamental principle underlying modern communication technologies. Unlike conventional approaches that first convert information into digital representations, RF Computing introduces a novel paradigm of information processing through direct transformations of RF signals within these domains. Building on this principle, we formally define RF Computing as follows.

**Definition 1** (RF Computing). *RF Computing is a computational paradigm that processes information through direct manipulation of RF signals within the RF space. Here the RF space refers to the space where RF signals exist and propagate. In this paradigm, RF signals serve as both information carriers and computational operands simultaneously.*

### 2.2 Computing Operations

A computing process of RF Computing can be formulated as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(x) * \overrightarrow{\boldsymbol{E}}_{\text{in}},$$

where $\overrightarrow{\boldsymbol{E}}_{\text{in}}$ and $\overrightarrow{\boldsymbol{E}}_{\text{out}}$ are the incident and outgoing RF signals, respectively, and $H(x)$ refers to the computing process. Note that this computing process can be viewed as an analogue of an instruction set in traditional computing systems, either logical or arithmetic, to perform calculation tasks in the RF space. According to the number of parameters in $H(x)$, RF Computing operations can be categorized into two types: basic operations and composite operations.

Basic operations are operations that transforms

RF signals in only one domain, which can be divided into the following five categories.

1) *Amplitude Transformation*. RF signals' amplitude can be manipulated by various RF Computing devices, e.g., power amplifiers and attenuators. This basic operation can be expressed as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(|E_0|) * \overrightarrow{\boldsymbol{E}}_{\text{in}}.$$

2) *Frequency Transformation*. The frequency of RF signals can be up-converted or down-converted by mixers. Also, the frequency of wideband signals can be cut off or filtered by using dedicated filters or frequency-selective devices. This operation can be expressed as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(f) * \overrightarrow{\boldsymbol{E}}_{\text{in}}.$$

3) *Propagation Direction Transformation*. RF signals can be manipulated to propagate towards any direction. This operation is typically achieved by transmission lines, antenna arrays, or gradient refraction materials, and can be formulated as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(\overrightarrow{\boldsymbol{k}}) * \overrightarrow{\boldsymbol{E}}_{\text{in}}.$$

4) *Phase Transformation*. The phase of RF signals varies within $[0, 2\pi]$, which can be manipulated by delay lines, phase shifters, and many other RF Computing devices. This operation can be expressed as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(\phi) * \overrightarrow{\boldsymbol{E}}_{\text{in}}.$$

5) *Polarization Transformation*. The polarization of RF signals can be transformed between different types, including linear, circular, and elliptical polarization. This operation can be achieved by polaroids and can be formulated as

$$\overrightarrow{\boldsymbol{E}}_{\text{out}} = H(\overrightarrow{\boldsymbol{e}}) * \overrightarrow{\boldsymbol{E}}_{\text{in}}.$$

Composite operations are the operations that transforms RF signals in more than one domain. A composite operation can be achieved in one shot or by a cascade of multiple basic operations. Both basic operations and composite operations are performed by RF devices in the RF space (where RF signals exist and propagate).

Information processing and exchange occur through transformations of RF signals, whether within the aforementioned five domains or through conversion from/to other types of information carriers. In the latter case, we define these conversions as the Input and Output of an RF Computing process. Typically, input devices include antennas, computer modules, and other devices that can produce EM radiation. Output devices include antennas, piezoelectric materials, and other devices that can convert EM waves into other information carriers, e.g., voltage or currents. Input and output operations can be formulated as:

$$\overrightarrow{\boldsymbol{E}}_{\text{in}} = H(|E_0|, \overrightarrow{\boldsymbol{e}}, \quad \omega, \overrightarrow{\boldsymbol{k}}, \phi_0) * F_{\text{in}},$$

$$F_{\text{out}} = H(|E_0|, \overrightarrow{\boldsymbol{e}}, \omega, \overrightarrow{\boldsymbol{k}}, \phi_0) * \overrightarrow{\boldsymbol{E}}_{\text{out}},$$

where $F_{\text{in}}$ and $F_{\text{out}}$ are information carriers outside the RF space. It is particularly noteworthy that through the formal definition of input/output operations, information processed via RF Computing can be seamlessly loaded from and stored to other information media. This preserves adherence to the fundamental compute-store architectural characteristic even in RF Computing integrated systems.

### 2.3 Typical Examples

Fig.3 presents two representative examples of RF Computing. These examples demonstrate the potential advantages of RF Computing as a viable alternative for solving traditional computing problems.

A typical category of examples is frequency information extraction in IoT applications. This operation is one of the most widely used operations in sensing and communication tasks, such as the Doppler frequency spectrum analysis in human activity recognition and demodulation in frequency division multiplexing communication. As shown in Fig.3(a), taking broadband signals as the input, the traditional approach first samples the signals and then performs a discrete Fourier transform (DFT) on the sampled data. By contrast, RF Computing exploits analog RF devices (e.g., leaky-wave antennas[53, 54] or SAW filters[32]) to directly transform the information in the frequency domain to other domains for easy extraction. In terms of the end-to-end energy consumption, RF Computing can achieve more than 99% energy reduction. For instance, extracting frequency information from LoRa signals via the traditional approach consumes 40 mW, whereas that of the RF Computing implementation consumes less than 100 μW[32], demonstrating a reduction of approximately 99.75%.

Fig.3(b) illustrates another example of solving the matrix multiplication problem. In a traditional digital implementation, one must fetch each weight and

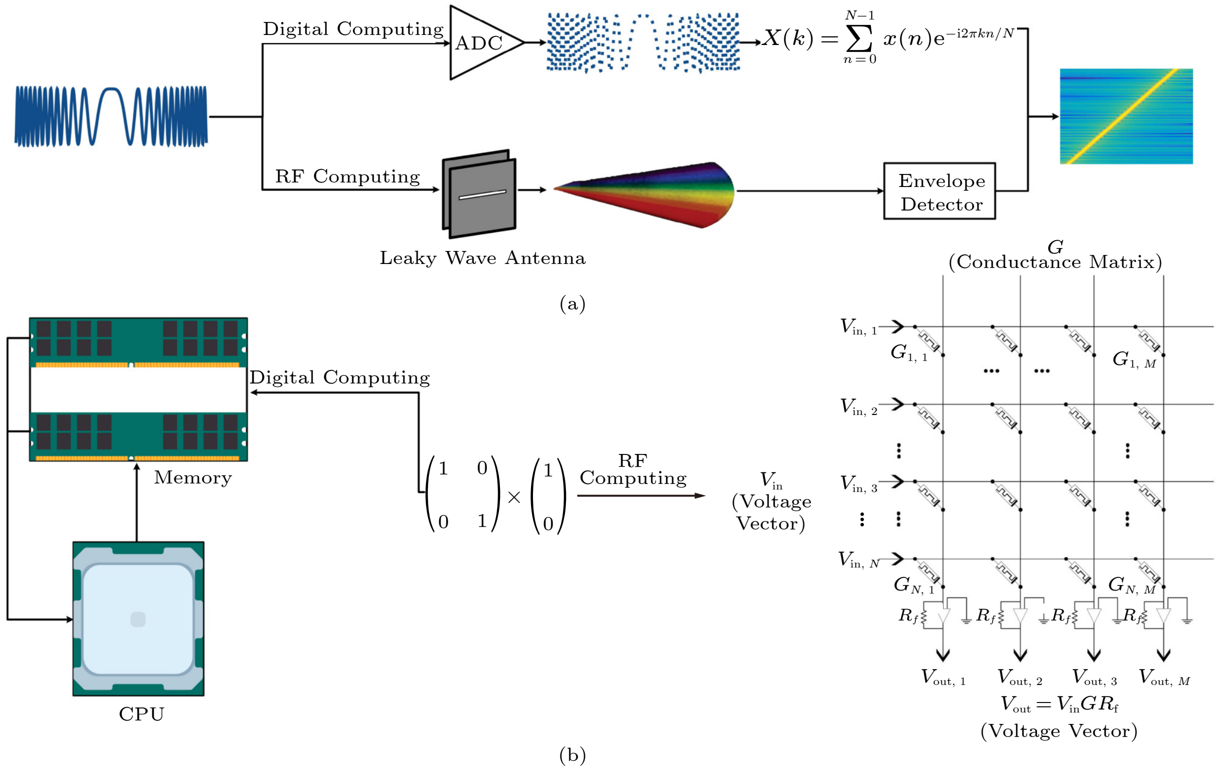


Fig.3. Cases of computing process using the methodology of RF Computing. (a) Spectrum analysis based on Discrete Fourier Transform or a leaky wave antenna. (b) Matrix multiplication based on CPU or memristor arrays. ADC: analog-to-digital converter.

activation from memory into a processor, perform the multiply-accumulate operations, and then write the results back. This process introduces frequent read/write cycles and thus significant speed overheads (e.g., 1 ms). Differently, RF Computing can exploit a memristor array to accomplish this problem: each memristor's conductance encodes a matrix weight, and when an incoming RF signal is broadcast across the array, the resulting currents are inherently summed along each column. As such, the matrix multiplication problem implemented by RF Computing can be accomplished almost instantaneously (e.g., 1 ns) in the RF space[55, 56].

### 2.4 Comparison with Traditional Computing

Table 1 compares RF Computing with traditional computing across multiple dimensions, including computation paradigm, information carrier, computational core, precision of computing, and energy efficiency. There may be other dimensions worthy of comparison, while we believe the dimensions listed in the table suffice to delineate the distinctive characteristics and contrasts between RF Computing and traditional computing. Nevertheless, an RF Computing system still fundamentally adheres to the existing architecture (e.g., the Von Neumann model), albeit introducing innovations in computational methodologies.

Based on the above understanding, we broaden our perspective by examining recent advances in IoT-related research, discussing how different approaches achieve RF Computing and exploring its potential advantages.

## 3 Status Quos of RF Computing

There have been numerous existing studies that embody the novel concept of RF Computing[57–68]. According to the function of RF Computing in a specific study, we classify the literature into three categories.

1) *RF Computing for Information Injection.* Com-

**Table 1.** Comparison Between RF Computing and Traditional Computing

| | Computational Paradigm | Information Carrier | Computational Core | Precision of Computing | Energy Efficiency |
|---|---|---|---|---|---|
| Traditional computing | Digital | Binary bit | Processor | High | Relatively low |
| RF Computing | Hybrid digital-analog | RF signal | RF device | Relatively low | High |

pared with other information carriers, RF signals are ubiquitous and exhibit a favorable propagation capability. This capability makes RF signals particularly suitable for information injection and propagation. In this category, information is introduced into the RF space via modality conversion, and translated from non-RF information carriers into RF signals[9, 27, 69–72].

2) *RF Computing for Information Transformation.* Different RF domains entail different information representation capabilities and processing overhead. In this category, information is converted and migrated from one domain of RF signals to another. By transforming information into a more suitable domain, higher computing efficiency and lower overhead can be achieved[7, 26, 32, 73–75].

3) *RF Computing for Information Augmentation.* Information augmentation is the computing process of enriching the information injected into RF signals. When the information is too weak to support reliable communication or sensing, one may harness the physical properties of RF signals to amplify the subtle variations within the RF space, thereby augmenting the injected information[3, 4, 37, 76, 77].

The rest of this section will review the existing work in the above-mentioned categories.

### 3.1 RF Computing for Information Injection

As a type of information carriers, RF signals can embed information we want to transmit into different domains. RF Computing harnesses the natural propagation capabilities of RF signals to enable ubiquitous information injection. As such, information can be seamlessly injected, transmitted, and accessed across the RF space. Moreover, RF Computing directly processes RF signals in the RF space, without requiring analog-to-digital converters (ADCs) to transform RF signals into the digital space for information embedding. Thus, the power consumption and system complexity will be exceptionally reduced compared with conventional digital computing. These features provide RF Computing based information injection with significant advantages in terms of energy efficiency and cost-effectiveness.

The representative RF Computing technique for information injection is backscatter. At its core, backscatter tags perform basic or composite operations and inject information on the incoming RF signals from the transmitter (Tx), without the need of sampling or generating RF signals. Existing backscatter technologies typically inject information into the three domains of RF signals, that is amplitude, phase, and frequency. The corresponding information injection techniques are On-Off Keying (OOK), Phase Shifting Keying (PSK), and Frequency Shifting Keying (FSK). 1) OOK is usually achieved by changing the state of RF Computing devices between reflecting and absorbing the incoming RF signals. This type of technique is mostly used in RFID systems[40], and further be extended to ambient and Wi-Fi backscatter[28]. 2) PSK is usually achieved by building a set of delay lines with different lengths or exploiting codeword translation[29] to enable different phase shifts, e.g., BPSK and QPSK. 3) FSK is usually achieved by shifting the frequency of the backscatter signals to another frequency band without collision with the incoming signals[30].

Different from many efforts performing basic operations and only injecting information into one domain, RF-Transformer[27] builds a programmable backscatter radio to inject information into multiple domains of the incoming RF signal. Specifically, RF-Transformer achieves this by employing a dedicated backscatter tag to perform the composite operation by altering both the phase and amplitude of signals. As illustrated in Fig.4, this capability allows IoT devices to synthesize different types of protocol-compliant backscatter signals sharing radically different physical-layer designs. Besides, RF-Transformer retains ultralow power consumption, which is 7.6x–74.2x less than active counterparts, such as Wi-Fi, Bluetooth, and LoRa.

However, when it comes to mmWave band, traditional information injection techniques may not function well. The main reason is that due to the high-frequency feature of the mmWave signals, backscatter signals will experience great path loss and exhibit little energy. The intuitive method is employing phased array antennas to focus the signal energy. Unfortunately, phased arrays are power-hungry, thus they are unaffordable for low-power IoT devices.

mmTag[69] tackles this problem by exploiting an RF Computing device, named Van Atta Array (VAA), to perform a composite operation by altering the phase, polarization and propagation direction of incident mmWave signals. As Fig.5 shows, a basic VAA can introduce phase offsets to the incident signals, so that the phase of backscatter signals is reversed. As such, backscatter signals will be retro-reflected. To inject information into RF signals, mm-

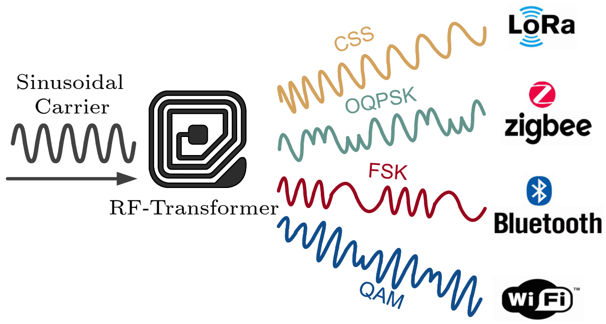


Fig.4. RF-Transformer backscatter design. CCS: Chirp Spread Spectrum, OQPSK: Offset Quadrature Phase Shift Keying, QAM: Quadrature Amplitude Modulation.

Tag adopts a simple RF switch to perform PSK and reverses the polarization of backscatter signals to avoid self-interference.

Millimetro[72] focuses on the problem of how to distinguish information injected by different tags. Millimetro finds that when tags inject information based on the OOK scheme, the backscatter signal will be converted to a sinc function after range-Doppler FFT, as Fig.6 illustrates. The primary frequency component of the sinc function is equal to the modulation frequency. Thus, Millimetro assigns unique OOK frequencies to different tags for distinguishing their injected information.

Different from the above-mentioned information injection schemes requiring active components in RF Computing devices, RoS[9] introduces another passive information injection method. RoS constructs different passive VAA stacks, where the information is represented by the layout of these stacks and can be injected into Radar Cross-Section (RCS) of backscatter signals. RoS can configure the information by adjusting the number and the layout of VAA stacks.

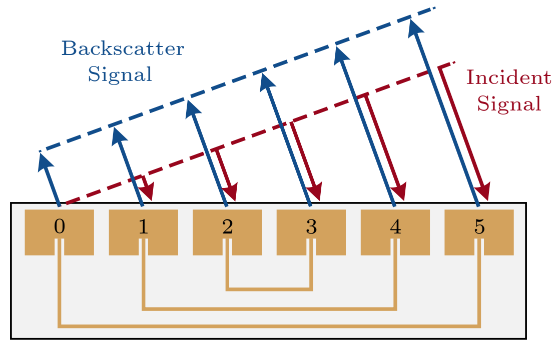


Fig.5. VAA used in mmTag[69].

## 3.2 RF Computing for Information Transformation

While information can be injected into different domains of RF signals, the associated costs of processing and extracting the information vary significantly depending on the domains, and computing devices involved. Different RF Computing devices exhibit distinct efficiencies and sensitivities when operating in specific domains. As such, strategically transforming information between domains can unlock higher computational efficiency and lower overhead. Pioneering research in RF Computing has already demonstrated the potential of information transformation across different domains of RF signals, which we will introduce in the followings.

Saiyan[32] transforms information from the frequency domain to the amplitude domain to enable signal demodulation on LoRa backscatter tags. Traditional digital approaches rely on operations such as downconversion, sampling, and FFT, which together consume over 40 mW—an impractical cost for low-power backscatter devices. In contrast, Saiyan repur-

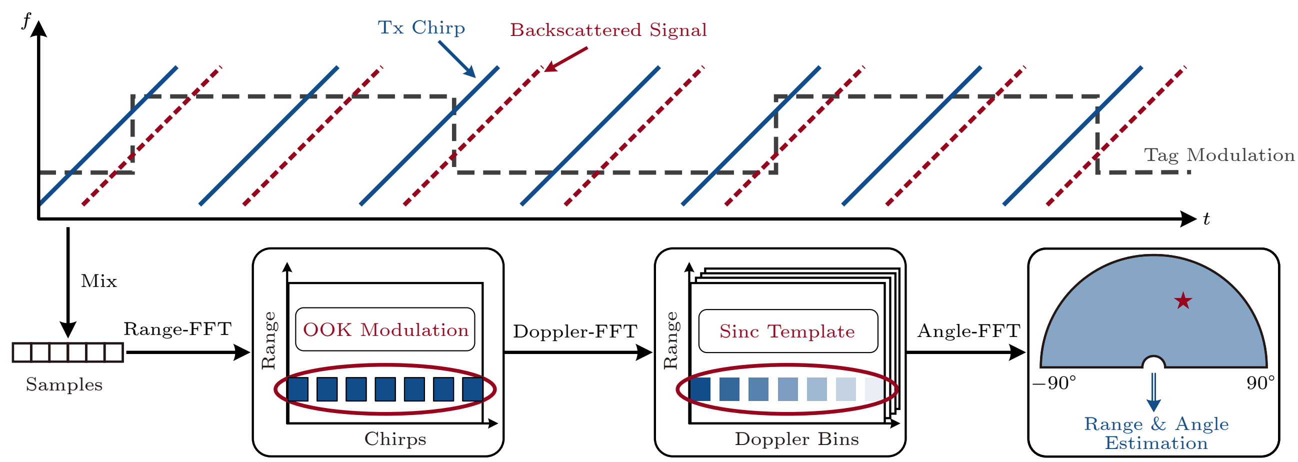


Fig.6. Concurrent tag localization and identification in Millimetro.

poses a surface acoustic wave (SAW) filter to perform signal differentiation, effectively transforming the frequency-domain information (i.e., linear frequency variation) into amplitude-domain information (i.e., linear amplitude variation), as illustrated in Fig.7. By doing so, the tags can decode the LoRa signals by simply detecting the peak amplitude with the envelope detector. This process avoids using power-intensive devices (such as downconverters, ADCs) and controls the system's power consumption at around 90 $\mu$W.

BIFROST[7] transforms information from the frequency domain to the propagation direction domain to enhance the availability of indoor WiFi localization. Specifically, BIFROST exploits leaky wave antennas (LWAs) to guide WiFi signals with different frequencies to different directions based on the dispersion effect (shown in Fig.8). Thus, a WiFi device can calculate its location by simply analyzing the spectrum of the received signals with the deployed LWAs, without the need for multiple WiFi access points.

MilBack[26] also employs LWAs to perform information transformation from the propagation direction domain to the frequency domain. Due to the reciprocity of LWAs, the frequency and propagation direction of the signal received by an LWA are coupled. Thus, MilBack integrates an envelope detector for the tag to identify the highest amplitude peak of the incident FMCW signal, where the time of the peak indicates the frequency, and in turn, the propagation direction of the signal. This approach enables demodulation on low-power tags without requiring complex digital processing.

### 3.3 RF Computing for Information Augmentation

Due to their ubiquitous nature, RF signals can interact with a variety of objects, ranging from RF Computing devices to human bodies. Thus, diverse types of information can be injected into RF signals during these interactions. However, the information is sometimes too weak to be distinguished from the noise or interference. As a result, the information is hard to use for supporting reliable communication or sensing. In these cases, dedicated RF Computing devices can be implemented to augment the injected information by exploiting the inherent physical properties of RF signals. Existing efforts demonstrate that the augmentations can amplify the subtle variations within the RF space and enable a more robust extraction of the injected information.

Meta-Sticker[37] develops a metamaterial sticker operating in the THz band to augment information regarding the ripeness of fruits. This information is hard to extract after THz signals interact with fruits, as THz signals attenuate significantly in water. To augment this information, Meta-Sticker attaches a metamaterial onto the fruit surface. Changes in the fruit's chemical composition affect the resonant frequency of the metamaterial, rendering its response highly sensitive to THz signals. This information augmentation not only amplifies the injected information about ripeness but also enables more precise and reliable sensing.

Similarly, MetaBioLiq[4] designs a wearable metasurface to augment information about human sweat by harnessing the resonance of the sweat liquid when interacting with high-frequency RF signals. Since microliters of sweat have a negligible presence on RF signal reflection, the injected information is difficult to be accurately extracted. Thus, MetaBioLiq employs a metasurface that resonates with the thin layer of sweat in contact with the skin, thereby significantly amplifying the information injected into the incoming mmWave signals.

ThermoWave[3] proposes a metamaterial to augment temperature information. In ThermoWave, the metamaterial can promptly equilibrate to the temperature of the attached target object, as Fig.9 illustrates. As the metamaterial's temperature changes, its molec-

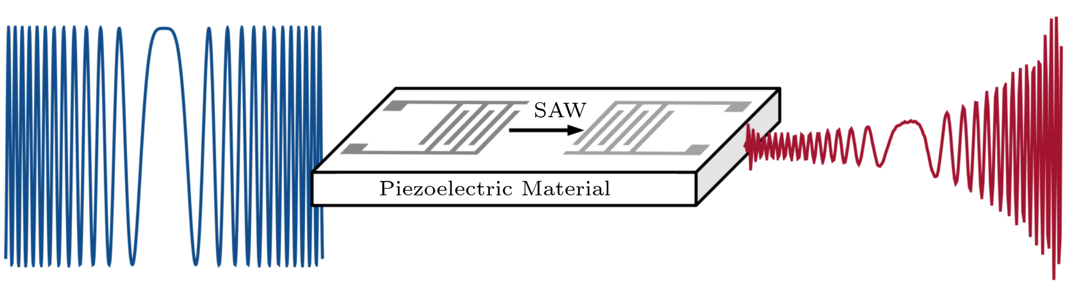


Fig.7. Saiyan[32] exploits a SAW filter to transform the information in the frequency domain to that in the amplitude domain.

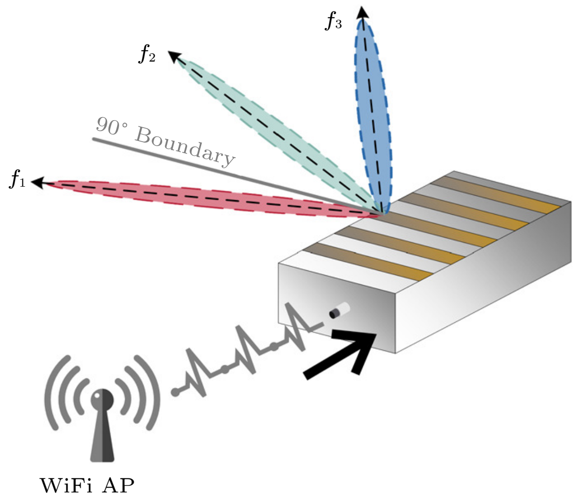


Fig.8. BIFROST[7] uses LWAs to transform the information in the frequency domain to the propagation direction domain.

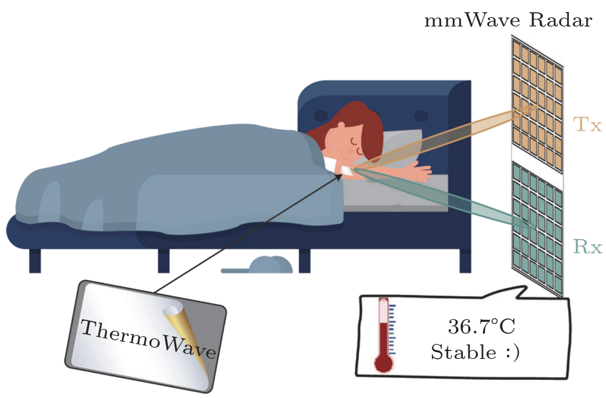


Fig.9. ThermoWave[3] uses a metamaterial to augment temperature information.

ular alignment shifts due to thermal expansion. This change in molecular alignment directly influences the frequency shift of the incoming mmWave signals and further augments the injected temperature information.

## 4 Open Problems and Future Directions

### 4.1 Unified Modeling and Quantification

To fully realize the potential of RF Computing and evolve it from fragmented innovations into a cohesive technological system, breakthroughs in foundational theories are critical. While nearly any RF-based signal transformation can be interpreted as a form of computation, not all such operations are practical or efficient, especially in IoT applications. Thus, the key challenge lies in establishing a unified model for RF Computing that enables precise quantification and evaluation.

This raises several fundamental questions. How should we characterize the information-carrying capacity of RF signals as computational objects? Can we develop a generalized RF Computing model that defines the computational capabilities of all participating RF devices? The definition in Section 2 defines RF Computing operations, which provides a starting point for modeling computing capabilities. However, unlike discrete computing, RF signals are continuous and high-dimensional, requiring more than just a classification of basic or composite operations. A robust model must also quantify how these operations modify signal characteristics.

Equally important is accounting for computational costs, including energy consumption, latency, and hardware expenses, all of which must be taken into account. Only then can we properly assess and compare different RF Computing approaches.

With the advancement in computational electromagnetics and RF integrated-circuit (RFIC), future exploration on RF device models and signal propagation models could help establish and refine the RF Computing model with realistic and multidimensional design considerations.

With such a model in place, we will achieve two key objectives. 1) Task-device matching: given an RF Computing task's input and output, determine which devices can perform the required operation. 2) Cost-optimized selection: when multiple devices qualify, evaluate them based on computational efficiency to identify the optimal option.

### 4.2 Generation and Discovery of RF Resources

As the fundamental building blocks of RF Computing systems, RF resources must be carefully engineered or selected. They are not always readily available or inherently suitable for computational tasks. For example, in long-range wireless sensing, information is often modulated in the frequency domain to combat channel fading, ensuring that signal features remain detectable for subsequent processing. In RF-based localization, wider signal bandwidth is preferred to achieve higher resolution, enabling precise RF-based distance measurement.

Therefore, how to acquire or tailor RF resources is a crucial problem. Two primary approaches exist. One of them is active generation, namely synthesizing customized RF signals to meet specific computational requirements. For instance, techniques from integrated sensing and communication (ISAC) wave-form design can be employed to jointly optimize RF signals to satisfy data transmission, sensing, and computation requirements in RF Computing. Passive discovery of RF resources is the other approach. The term passive is to emphasize that the goal of detecting and leveraging existing RF resources should be achieved under strict constraints, particularly low energy consumption. Meanwhile, passive discovery faces a unique hurdle: an RF device generally adheres to standardized communication protocols, whereas the signals to be discovered may follow different formats. It is clearly challenging to detect, identify, and manipulate such signals with a standardized device. Cross-technology communication research in the IoT community[45–51] has offered partial solutions, while a robust framework for interoperable RF resource discovery remains an open problem.

### 4.3 Computing in the Analog Domain

Undoubtedly, analog computing represents the most innovative aspect of RF Computing. Existing research has fully demonstrated its outstanding advantages, such as low energy consumption and high efficiency. However, analog computing also has inherent limitations, including limited precision and a restricted computable range.

The issue of limited precision is not an absolute drawback. The key research issue lies in how to solve practical problems with limited-precision computation. Notably, many IoT sensing applications do not demand high precision of computation. Thus it is indeed crucial to align application requirements with the achievable capabilities of RF Computing. This often involves efforts to adapt problem-solving approaches to leverage the strengths of analog computing while mitigating its weaknesses. For instance, one can integrate multiple redundant elements to correct the errors brought by low-precision analog computing, thereby achieving an overall precision close to that of conventional digital systems[78]. Alternatively, a tailored deep-learning framework can be trained to model analog non-idealities, such as component mismatches or noise, so as to preserve high-precision performance even when operating on inherently low-precision hardware[79]. These examples demonstrate that, by combining these hardware and algorithm strategies, computing in the analog domain can deliver digital-comparable precision to support many applications.

As for the constrained computable range, it is an easily overlooked challenge. Analog computing is built upon the physical properties of RF components. It is worth noticing that such physical properties may vary with input signals, leading to computational performance that fluctuates with input conditions. Such variability is generally undesirable, as it makes it difficult for system designers to design deterministic algorithms, and program behavior may become unpredictable due to hardware uncertainties.

The work in [70] provides a concrete example: the researchers attempted to use varactor diodes to achieve linear conversion from the capacitance of varactor diodes to the output signal phase by adjusting the input voltage. However, this linearity only holds within a limited capacitance range, as Fig.10 illustrates. Thus, the input voltage range is also bounded, which can be viewed as a restricted computable range. Designing analog computing schemes that effectively utilize this limited operational scope remains a highly challenging task.

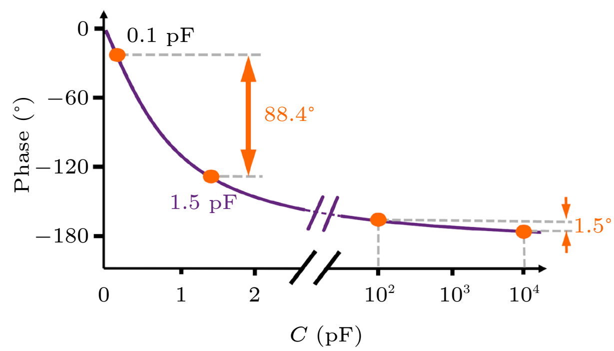


Fig.10. Nonlinearity between the capacitance of varactor diodes and the output signal phase.

To address the above-mentioned challenge, solutions could come from the area of circuit systems. For instance, at the circuit level, designers can optimize topologies, carefully model the parasitic capacitance and resistance, and insert dynamic compensation networks to broaden the linear region. By fully leveraging circuit-system techniques, RF Computing can fully enjoy the energy and latency benefits within a reliably bounded operational domain.

### 4.4 Programming of an RF Computing System

Through our previous discussion, we may reach a consensus that both digital and analog computing have their respective advantages and limitations. Therefore, future RF Computing systems will likely be built on a hybrid computing architecture with both digital and analog components. Techniques such as analog-digital partitioning, dynamic voltage and frequency scaling, and hardware-software co-design enable precise allocation of tasks between analog front-ends and digital processors. The design goal of such a system is to accomplish specified tasks or solve targeted problems. Such a task typically involves transforming a given input signal into the desired output signal. Interestingly, with the introduction of analog computing, there are often multiple feasible solutions to achieve this objective. The examples in Figs.3 and 7 have indicated this fact. For programming of an RF Computing system, the key of research lies in the methodology of developing such solutions, which involves answering the following three questions.

1) *Computational Methodology and Workflow.* For a given task, what are the computational methods and processes? How do we determine which parts of the system should be handled by digital components and which by analog components, and what are their respective computational functions?

2) *Performance Metrics and Resource Constraints.* While fulfilling the computational requirements, how should performance targets and resource constraints be quantified? Furthermore, how can these requirements and constraints be decomposed and translated into specifications for each digital and analog component?

3) *Component Selection and Optimization.* Under the conditions of meeting functional, performance, and resource constraints, what components are available, and how should they be selected?

To answer the above questions, one can draw on circuit-system expertise to model RF Computing as a modular signal-processing chain. A high-level process is as follows: first, use block-diagram and network-theoretic abstractions to partition analog and digital tasks; next, quantify performance metrics and resource constraints; and finally, validate through co-simulation and iterative optimization. Based on this programming and modeling framework, RF Computing operations can be systematically generalized and composed into a broad class of well-defined and purposeful computations.

### 4.5 Debugging and Testing of an RF Computing System

Debugging and testing such a hybrid RF system presents another intriguing challenge. Since the programming process involves both algorithm design and hardware selection, the system's behavior depends on the interplay of these two aspects. When functional issues arise, the first critical step is to determine whether the problem lies in the algorithm or the hardware.

Debugging tools and testing platforms are important in regard to the complexity of the above problems, while the primary challenge here is the lack of a robust method to decouple these two factors for isolated analysis. If the issue stems from the algorithm, it may require adjustments— or even a complete redesign— of the solution. On the other hand, if the problem is hardware-related, further testing is needed to discern whether it arises from a functional defect (e.g., a faulty component) or an incorrect selection during the hardware configuration phase.

Many other important directions exist, though we can only briefly outline them here due to space constraints. With the advancement of RF Computing, IoT applications will reach new heights. By fully leveraging the potential of RF Computing, we may utilize limited signal feature spaces to carry more information, enabling integrated sensing-communication-computing or multi-purpose sensing applications.

At the cross-disciplinary areas, numerous exciting challenges await exploration, including but not limited to uncovering the RF Computing capabilities of existing materials and developing new materials specifically optimized for RF Computing.

### 4.6 Initiatives for Community Building

Despite rapid advances in RF Computing, research efforts in this domain remain fragmented. The lack of standardized RF devices and evaluation methodologies severely compromises reproducibility and impedes fair comparison across studies. Compounding this issue, researchers frequently develop proprietary hardware platforms, resulting in fragmented silos and unnecessary duplication of efforts. To address these challenges, we advocate for community-wide adoption of open datasets and shared resources as fundamental enablers of progress.

*Standardized Hardware Platforms.* The community should collectively develop and maintain a library of standardized RF components, including RF front-ends and backscatter tags, accompanied by comprehensive design documentation. Such standardized platforms would enable researchers to isolate algorithmic performance from hardware-specific variations while eliminating redundant development efforts.

*Unified Evaluation Framework*. A critical need exists for an open-source evaluation toolkit encompassing data collection, preprocessing, and performance measurement capabilities. This framework would ensure consistent methodology application and enable direct cross-study comparisons.

*Open Datasets Initiative*. We strongly encourage researchers to contribute RF datasets spanning multiple frequency bands (sub-6 GHz to mmWave), diverse propagation environments (urban, indoor, rural), varied mobility scenarios, and different protocol stacks. Well-annotated, publicly available datasets will significantly enhance reproducibility and accelerate knowledge sharing.

*Benchmarking Standards*. The community must establish clearly defined benchmark tasks targeting fundamental RF Computing challenges—including power efficiency, throughput, and latency. These should incorporate reference implementations, standardized evaluation pipelines, and performance baselines. Such benchmarks will provide meaningful comparison metrics for emerging RF Computing approaches while promoting best practices in experimental design.

## 5 Conclusions

RF Computing has emerged as a revolutionary approach that seamlessly integrates sensing, communication, and computation through native RF signal manipulation. By processing information directly in the RF domain, this paradigm offers unprecedented energy efficiency and performance advantages over traditional digital systems. However, significant challenges remain in developing unified theoretical models, establishing standardized evaluation methodologies, and creating robust hybrid analog-digital architectures. The research community should focus on collaborative efforts to build shared resources, benchmark tasks, and open datasets to accelerate progress. As these foundational elements fall into place, RF Computing is poised to transform IoT applications, enabling ubiquitous, low-power smart systems while opening new research avenues in electromagnetics, materials science, and edge computing. The realization of this potential will require sustained interdisciplinary collaboration and systematic investigation of the identified open problems.

**Conflict of Interest** The authors declare that they have no conflict of interest.

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