Abstract—Wireless data aggregation (WDA), referring to aggregating data distributed at devices, is a common operation in 5G-and-beyond networks for supporting applications related to distributed sensing, learning, and consensus. Conventional WDA techniques that are designed based on a separated-communication-and-computation principle encounter difficulty in meeting the stringent throughput/latency requirements imposed by emerging applications (e.g., auto-driving). To address this issue, over-the-air computation (AirComp) is being developed as a new WDA solution by integrating computation and communication. By exploiting the waveform superposition property of a multiple-access channel, AirComp turns the air into a computer for computing and communicating functions of distributed data at many devices, thereby dramatically accelerating WDA. In view of growing interests on AirComp, this article provides a timely overview of the technology by discussing basic principles, advanced techniques, applications, answering frequently asked questions, and identifying promising research opportunities.

I. INTRODUCTION

As mobile Internet penetrates every aspect of our daily lives and society, 5G-and-beyond networks aim at supporting a wide range of new mobile applications ranging from ultra-high definition video streaming to auto-driving to augmented reality. To support the applications with demanding throughput/latency requirements, 5G-and-beyond designers have set the ambitious goals of achieving fast access speeds in the order of one gigabit per second, high densities in the order of one million devices per square kilometre, and low latency within ten milliseconds. To achieve these goals has been driving researchers to develop a series of new technologies in wireless communications such as mobile edge computing, millimeter-wave communications, small cells, and massive multiple-input multiple-output (MIMO). However, even with the technological breakthroughs, practical 5G systems can attain their goals only under special settings while the average speeds fall in the range of 150-200 Mb/s and latency in the range of 10-100 milliseconds. This has prompted an increasing number of researchers to depart from the traditional design using a generic criterion and explore the designs of application-specific wireless technologies integrating disciplines such as machine learning, computing, and communications.

Aligned with this direction, we are interested in a specific class of applications requiring an edge server (which can be a base station) to aggregate data distributed at devices with wireless connectivity, termed wireless data aggregation (WDA). Such applications include vehicle platooning, drone swarm, sensing, and distributed learning. In such applications, a server is interested in computing a function of distributed data generated by devices. Such data include artificial intelligence (AI) model updates in distributed learning, accelerations and velocities in vehicle platooning or drone swarm, and temperature/humidity/chemical-levels in sensing. The applications are either data intensive (e.g., distributed learning) or latency critical (e.g., vehicle platooning). The requirements have motivated researchers to develop a new technology, called over-the-air computation (AirComp), to enable efficient WDA over many devices. The basic principle of AirComp is to exploit the waveform superposition property of a wireless channel to realize over-the-air aggregation of data simultaneously transmitted by devices. Simultaneous transmission in AirComp allows each device to access all radio resources instead of only a fraction of them as in the conventional orthogonal multiple access schemes (see Fig. 1), thus accelerating WDA.

A vivid interpretation of the key feature of AirComp is to harness interference to help functional computation, thereby turning the air into a computer.

The basic principle of AirComp is not new and has been applied in the past in physical layer network coding, compute-and-forward relaying, and remote sensing. As attempts to tackle the challenges faced in supporting 5G-and-beyond applications, recent research on AirComp focuses on developing a versatile WDA technology by advancements in different directions including power control, spatial multiplexing, channel feedback, and multi-cell cooperation. In view of growing interests on AirComp, this article provides a comprehensive introduction of the new technology covering the basic principles, advanced techniques, applications, and research opportunities.

II. AIRCOMP FUNDAMENTALS

A. Uncoded AirComp

The popular implementation of AirComp is simple as it required no coding. The basic idea is to exploit the analog-wave superposition property of a multiple-access channel (MAC). As a result, the signals simultaneously transmitted by synchronized devices are added over-the-air and arrive at the receiver as weighted sum, called the aggregated signal, with weights being the channel coefficients. As shown in Fig. 2, the two essential operations for uncoded AirComp are linear-analog modulation and channel pre-compensation at each transmitter. The former modulates the data values into the magnitudes of the carrier signals; the latter compensates for heterogeneous channel fading of different links. As a result, each component part of received signal is the transmitted...
data scaled by a pre-determined factor. Setting the factor uniform for all signals, called magnitude alignment, reduces the aggregated signal to the desired average of transmitted distributed data, realizing the AirComp of an average function.

With appropriate data pre/post-processing, the capability of AirComp can go beyond averaging to compute a class of so-called nomographic functions \[4\]. Supposing there are \(K\) devices, a monographic function has the following form:

\[
y = \text{post-processing} \left( \sum_{k=1}^{K} \text{pre-processing}_{k}(\text{data-value}_{k}) \right).
\]

Typical functions include arithmetic mean, weighted sum, geometric mean, polynomial, and Euclidean norm. Consider AirComp of geometric mean as an example. The pre-processing at each device transmitter \(k\) is to compute the logarithm of a data-value, \(\text{log}(\text{data-value}_{k})\); the post-processing at the receiver is to compute the exponential function of the received sum, namely post-processing(\(\cdot\)) = \(\exp(\cdot)\). As a result, the receiver obtains the geometric mean of distributed data: \(y = \sqrt[1/\text{V.S.}]{{\text{data-value}_1 \times \cdots \times \text{data-value}_K}}\).

Without protection by channel coding, the operation of uncoded AirComp is exposed to signal distortion caused by channel fading and noise, channel estimation error, and synchronization error as illustrated in Fig. 2. The distortion of the received functional value can be suitably measured using the mean squared error (MSE) with respect to the ground truth, which is a commonly used performance metric for AirComp and termed the computation error.

B. Is Coding Necessary?

In a conventional point-to-point communication system, source and channel coding are essential for optimizing the tradeoff between the transmission rate of data symbols and their distortion. The counterpart of transmission rate in an AirComp system is the computation rate that is defined as the rate of functional values that can be computed and communicated from devices to the server. A natural question arises: Are coding necessary for an AirComp system to achieve the optimal tradeoff between computation rate and distortion (i.e., MSEs of received functional values)? A surprising answer was provided in the landmark work in \[3\] from the information-theoretic perspective that coding is unnecessary for AirComp over a Gaussian MAC with independent Gaussian sources. In other words, uncoded AirComp is optimal in this case. However, coding can help in other cases. In particular, the integration of AirComp with lattice coding can outperform uncoded AirComp in the case with correlated Gaussian sources \[5\] or in the case with discrete sources, which generate sampled and quantized data \[6\]. Last, it is worth mentioning that from the perspective of safety against attackers and eavesdroppers, the transmitted signals can be scrambled at devices using random sequences, which does not affect the feasibility of AirComp so long as their sequences are identical.

In the remainder of this article, we focus on the uncoded AirComp as it is commonly used in practice due to its simplicity and proven optimality for the case of independent Gaussian sources over a Gaussian MAC.

III. ADVANCED AIRCOMP TECHNIQUES

Recent research on AirComp focuses on advanced techniques aiming at boosting the computation rates, reducing computation errors, or supporting large-scale deployment.

A. Power Control for AirComp

In AirComp, channel inversion is usually implemented at the transmitters by adjusting their transmission power to achieve magnitude alignment at the receiver. However, when one or more individual channels are in deep fade, enforcing the magnitude-alignment constraint can result in large AirComp errors. The reason is that a very small alignment factor has to be chosen to make it possible for all devices including those with weak links to perform channel inversion, which weakens the aggregated signal and hence amplifies the negative effect...
of channel noise. This suggests that uniform channel inversion may not be always desirable and the optimal power-control policy for AirComp should be adapted to multiuser channel states. Recently, it was shown in [7] that the optimal policy for the case of independent sources exhibits a “binary” structure. Specifically, devices with weak channel gains, which are below a derived threshold, should transmit with full power while others should perform channel inversion. The departure of such power-control policy from the optimal “water-filling” one in a conventional multiuser communication system highlights the difference between WDA and sum-rate maximization.

**Some research opportunities:**

- **Optimal power control for AirComp with correlated sources:** Source correlation usually exists in practical applications such as distributed sensing. In this case, the optimal power control for AirComp remains unknown while the discussed binary strategy from [7] is optimal only in the case without source correlation. The challenge lies in that the correlation requires the power control at different devices to be jointly designed. The associated optimization problem is much more sophisticated than the counterpart without source correlation.

- **Robust power control for AirComp:** In practice, inaccuracy usually exists in the channel estimation process. Power control using imperfect channel-state information (CSI) can lead to large AirComp errors. Therefore, it is important to characterize the effect of imperfect CSI on the AirComp performance. Leveraging the results, robust power control algorithms can be designed to optimize the worst-case AirComp performance.

**B. MIMO AirComp**

Some emerging WDA applications are either latency sensitive (i.e., sensing data aggregation using a UAV mounted fusion center) or data intensive (i.e., distributed learning). To support such applications motivates the acceleration of Air-
Comp by spatial multiplexing over MIMO channels, or equivalently the realization of vector-function AirComp. MIMO AirComp differs from its single-antenna counterpart in two ways. First, the channel-inversion power control of the latter is replaced with zero-forcing precoding. Second, the multi-antenna server attempts to apply receive beamforming, called aggregation beamforming, to achieve simultaneous magnitude alignment (or simultaneous aggregation) of spatially multiplexed multiuser signals so as to receive parallel functional streams; such an operation is unavailable for a single-antenna server. One key challenge on designing MIMO AirComp is to optimize the aggregation beamformer for minimizing the MSE of vector-function AirComp. One approximate solution was obtained in [8] which is presented on a Grassmann manifold where the subspace corresponding to a MIMO channel matrix is mapped to a singe point and so is the aggregation beamformer. By approximate MSE minimization, the beamformer is designed as the weighted sum of individual MIMO channel subspaces with the weights determined by the channel strengths. As illustrated in Fig. 4, the geometric interpretation is that the optimal aggregation beamformer tends to align closer with relatively noisy MIMO channels and less with the less noisy ones, so as to equalize the noise levels in different channels to achieve overall AirComp error reduction.

Some research opportunities:

- **Optimization of precoders and aggregation beamformer.** The optimal design for aggregation beamforming remains unknown. As channel-inversion power control is sub-optimal for single-antenna AirComp, zero-forcing precoding is sub-optimal for MIMO AirComp. To minimize the MSE, it is desirable to jointly optimize the precoders at devices and the aggregation beamformer at the server, which appears to be a complex problem to solve.

- **Diversity-multiplexing tradeoff for MIMO AirComp.** For conventional MIMO communications systems, there exists a fundamental diversity-multiplexing tradeoff in terms of reliability and sum-rate performance. A similar tradeoff also holds for MIMO AirComp where the spatial degrees-of-freedom can be applied either to spatially multiplex functional streams or to reduce their errors. Quantifying the tradeoff helps the understanding of the fundamental limit of MIMO AirComp.

C. Multi-cell AirComp

In next-generation IoT, the relevance of AirComp to different types of applications (see Section IV) and its being a promising low-latency solution suggest the need of considering its large-scale deployment in a multi-cell network. Multi-cell AirComp can be implemented in two modes, namely hierarchical AirComp and coordinated AirComp. In hierarchical AirComp, a centralized server aggregates AirComp results output by local servers connected by backhaul links to scale up the aggregation gain, e.g., training a larger model or exploiting a larger dataset in the context of distributed edge learning. On the other hand, coordinated AirComp aims at supporting coexisting WDA tasks in different cells, each of which is characterized by its application, data type, and target function. The coexisting tasks in coordinated AirComp are exposed to inter-cell interference. This calls for interference management by multi-cell coordination to balance the errors in the coexisting tasks. While multi-cell AirComp is an open area, an initial attempt has been made in [9] on understanding the performance limit of coordinated AirComp by quantifying the Pareto boundary of the multi-cell MSE region.

Some research opportunities:

- **Hierarchical AirComp with limited cooperation overhead:** The centralized control of the operations at a large number of nodes can incur excessive signaling overhead (e.g., CSI feedback) especially in the case of MIMO channels. To reduce the overhead, it is desirable to implement part of the operations (e.g., precoding and aggregation beamforming) in a distributed manner.

- **Performance and techniques for coordinated MIMO AirComp:** The Pareto boundary of the multi-cell MSE region in this scenario is much more sophisticated than that for single-antenna network studied in [9]. Specifically, the complexity arises from the need of designing interference management techniques by the joint optimization of precoders, aggregation beamformers, and power control across the whole network.

D. AirComp with Digital Modulation

The basic analog AirComp design introduced in Section II requires linear analog modulation, which implicitly assumes that the transmitter can modulate the carrier waveform as desired, freely setting the waveform magnitude as arbitrary real number. However, digital modulation such as quadratic amplitude modulation (QAM) is widely used in practical systems such as LTE and 5G, and most existing devices come with embedded digital modulation chips that cannot support an arbitrary modulation scheme. To address this issue, an idea, called digital AirComp, was proposed in [10] that a QAM modulator can be treated as a quadratic linear analog modulator with complex amplitude quantization. The idea allows AirComp to be implemented on popular transceiver architectures such as an OFDM transceiver as demonstrated in an application to distributed edge learning in [10]. The digital solution therein features one-bit gradient quantization at devices and a majority-vote based gradient-decoding at the server, which is experimentally shown to achieve comparable learning performance as its analog counterpart, demonstrating the effectiveness of digital AirComp.

Some research opportunities:
Digital AirComp with adaptive modulation: In digital AirComp, the modulation order (or quantization level) serves as a control variable regulating the tradeoff between the functional-value resolution, modulation complexity, and robustness against channel noise. Optimally adapting the modulation order to the channel state and a latency requirement can enhance the performance of digital AirComp.

Effect of quantization distortion: The effects of quantization errors introduced by digital AirComp on the ultimate computation performance have not been theoretically understood. A rigorous analysis of such effects for different applications helps further optimization of the quantization scheme in the context of AirComp.

E. CSI Feedback for AirComp

The server requires the CSI of individual uplink channels in order to deploy the aforementioned AirComp techniques such as power control, aggregation beamforming, and interference management. The usual approach of acquiring the CSI is to let the server sequentially estimate individual channels or devices to feed back their CSI when channel reciprocity is available. However, this may cause excessive latency and overhead when there are many devices. A more intelligent approach is to apply AirComp to accelerate the CSI-feedback process. In other words, AirComp is applied not only in WDA but also in acquiring CSI needed for WDA. This approach was demonstrated in [8] for enabling aggregation beamforming for MIMO AirComp. Assume the availability of channel reciprocity that allows devices to have the CSI of their individual uplink channels. The feedback design in [8] involves each device transmits an analog modulated signal computed from its individual CSI so that an over-the-air aggregated signal received by the server can be used to directly extract the desired aggregation beamformer. Note that the design bypasses CSI acquisition to directly receive the beamformer by simultaneous “one-shot” transmissions by devices. Consequently, the CSI-acquisition overhead is independent of the number of devices.

Some research opportunities:

• Robust CSI feedback: A key drawback of the discussed “one shot” feedback scheme is that the acquired aggregation beamformer is exposed to the perturbation by channel noise and interference. This can severely degrade the AirComp performance and calls for robust feedback design. A possible solution is to provide feedback protection by scrambling analog feedback signals or even apply a coding techniques customized for AirComp (e.g., lattice coding) as introduced in Section II-B.

• CSI-free AirComp: An alternative solution to avoid CSI feedback is to develop CSI-free AirComp techniques. One possible idea is to embed the source data into the distribution of transmitted signals such that the desired function of the distributed data is embedded into the distribution of the aggregated signal. The function can be retrieved by distribution-parameter estimation at server using tools from statistical inference [11].

IV. APPLICATIONS – SENSING, LEARNING, CONSENSUS

AirComp is envisioned to have a wide range of applications related to the areas of distributed sensing, learning, and consensus, as illustrated in Fig. 5 and discussed in the following.

A. Distributed Sensing

Future IoT is expected to automate various operations of our society ranging from manufacturing to healthcare to traffic control. To this end, IoT networks need to aggregate distributed sensing data from a large number of sensors, which are used for inference and making decisions on how to control the physical environment via actuators. One challenge faced by next-generation distributed sensing is fast WDA in scenarios
with high mobility and intensive data uploading [8], [12], [13]. As illustrated in Fig. 5, a fusion center mounted on an unmanned aerial vehicle (UAV) or ground vehicle can be deployed to monitor a wild environment or a city by collecting environmental sensing data (e.g., airflow, temperature, pollution, and humidity). Due to the short center-sensor contact and the potential high density of sensors, the conventional “separated-communication-and-computation” approach may not be able to meet the stringent latency requirement for fast WDA.

The problem can be solved using AirComp. In many IoT applications, a fusion center is interested in knowing a specific function of distributed data instead of individual data samples. For example, for environmental monitoring, the sensor network should monitor the average value of noisy temperature readings measured by sensors distributed over a particular area. As another example, in a disaster avoidance system, the interested functional value is the maximum chemical level or temperature over the sensor readings. The integrated functional computation and wireless transmission enables AirComp to support fast WDA in large-scale distributed sensing with multi-access latency independent of the network scale.

B. Distributed Edge Learning

Driven by gaining low-latency and privacy-aware access to rich mobile data for intelligence distillation, recent years have witnessed the spreading of AI algorithms from the cloud to the network edge, resulting in an active area called distributed edge learning [2]. As illustrated in Fig. 5, a typical algorithm for training an global AI model iterates between two steps: 1) the server receives distributed model updates transmitted by devices over a MAC and applies their average to update the global model; 2) the server broadcasts the updated global model to devices for updating using local data. Step 1) results in a communication bottleneck due to the high dimensionality of each model update (usually comprising millions to billions of parameters) and the multi-access by many devices. Overcoming the bottleneck is important for alleviating the congestion of the air interface also shared by other types of services and reducing the learning latency for mission critical applications e.g., learning how to deal with “black-swan” events in auto-driving. The conventional orthogonal/non-orthogonal multi-access schemes are inefficient as their underpinning philosophy of interference being a foe causes the required radio resources to scale linearly with the number of devices. To solve the problem intelligently, AirComp has been recently developed as a new air-interface solution for fast model update aggregation in distributed edge learning [10], [14]–[19]. Thereby, the server directly receives the aggregated version of analog modulated local models/stochastic-gradients simultaneously transmitted by devices. Compared with the conventional orthogonal multi-access, AirComp can reduce the communication latency by a factor approximately equal to the number of devices without significant loss of the learning accuracy, as shown in Fig. 6.

Besides the benefit of low multiple-access latency, exploiting AirComp for distributed edge learning has an additional advantage in data privacy enhancement. Note that the risk of privacy leakage is not completely eliminated by the distributed learning protocol under the orthogonal multiple-access schemes. This is because that with advanced model inversion attacks [20], it is still possible to infer the local training data from the local model updates. As a remedy, AirComp makes the eavesdroppers can only access to the aggregated updates where each private local one is hidden in the crowd. Moreover, the random perturbation imposed by the channel noise on the aggregated updates is another mask for free that can protect the data privacy [21].

C. Distributed Consensus Control

Distributed consensus control pertains to a scenario where multiple agents interact with each other with the aim of reaching an agreement over a set of variables of common interest. It is a key operation in a wide range of applications such as vehicular platooning and swarm UAV/robot formation control. For example, in vehicular platooning, all the participating vehicles need to reach a consensus on common driving variables of the platoon including its velocity, acceleration, and trajectory. To this end, each agent needs to iteratively update its information state (IS), referring the settings of its driving variables, by running an iterative consensus protocol. As illustrated in Fig. 5, each iteration of such a protocol comprises 1) a communication step where each agent transmits its IS to other members of the platoon, and 2) a computation step where an agent updates its IS with the average of those of others. The consensus is reached if all IS’s converge to the same value. For mission critical applications such as vehicle platooning or swarm UAV, the latency allowed for distributed consensus is ultra-low (e.g., of the order of 1-10 milliseconds). This is essential to ensure the safety of a platoon/swarm usually travelling at a high speed and endow on it the ability of responding to unforeseen events and adapting to complex traffic conditions. The efficient implementation of the consensus protocol using AirComp, which merges the communication and computation steps in each round, can shorten the per-round latency and thereby accelerating the convergence (see e.g., [22]). Specifically, in each round, agents simultaneously broadcast their ISs after analog modulation; as a result, provisioned with full duplexing capability, the agents directly received the average of peers’ IS’s and updated its own IS with the average. The “one-shot” simultaneous transmission by all agents instead of time/frequency division multi-access can dramatically reduce the latency when there are many agents. As a result, a vehicular platoon or UAV swarm can travel at a higher speed or have a larger size.

It is worth noting that AirComp for distributed consensus needs to be implemented in a fully decentralized manner, in contrast to those for distributed sensing and learning that are coordinated by edge servers. This is because that, each agent plays a dual role in distributed consensus systems. On one hand, each agent is a client participating in AirComp by contributing its local IS’s to other agents. On the other hand, each agent is also a fusion center that needs to compute a function of the local IS’s from other agents. Therefore, the pre- and post-processing at each agent need to be carefully designed, at each iteration, to perform decentralized AirComp
Figure 6. Performance comparison between AirComp and OFDMA in test accuracy (a) and communication latency (b). A convolutional neural network is trained on the distributed MNIST data for handwritten digit recognition, where the update aggregation is performed by AirComp or OFDMA. For AirComp, model parameters are analog-modulated and each sub-channel is dedicated for single-parameter transmission; truncated-channel inversion under the transmit-power constraint is used to tackle the channel fading. For OFDMA, model parameters are first quantized into a bit sequence (16-bit per parameter). Then adaptive MQAM modulation is adopted to maximize the spectrum efficiency while maintaining the target bit-error-rate of $10^{-3}$.

in the presence of channel fading and noise. Otherwise, the IS’s at different agents may fail to reach consensus. Designing decentralized AirComp for consensus is a more challenging problem than centralized AirComp for sensing and learning, as it goes beyond the “one-shot” computation of a pre-determined function. Moreover, it needs to account for the interdependence between the multiple functions to be computed at different iterations along the IS update-trajectory for consensus guarantee.

V. FREQUENTLY ASKED QUESTIONS

While various enabling AirComp techniques have been recently developed in the literature, some basic questions regarding the generality and practicality of AirComp are frequently asked. In this section, an attempt is made to shed light on some FAQs.

**Question 1:** Is it possible to compute functions other than nomographic ones?

**Answer:** It is proved in [4] that any continuous function of $n$ variables can be decomposed into a summation form of at most $(2n+1)$ multiple nomographic component functions. The result implies that any function of $n$ variables is AirComputable via at most $(2n+1)$ channel uses with each channel use applied to computing a single monographic component function. When the number of component functions exceeds $n$, it is more efficient to perform WDA using a conventional orthogonal multi-access scheme (e.g., TDMA) for sequential communication and computation, which requires only $n$ channel uses. Otherwise, AirComp is more efficient.

**Question 2:** Does synchronization pose an obstacle in AirComp implementation?

**Answer:** AirComp requires time synchronization in devices’ transmissions. There exists a rich set on practical synchronization techniques. In particular, uplink synchronization in LTE systems relies of a so-called “timing advance” mechanism. Specifically, each device estimates the propagation delay and then transmits ahead of time (with a negative time offset equal to the delay) so that the signal always arrives at the base station within the allocated time slot regardless of the device’s location. The synchronization accuracy is proportional to the bandwidth of the synchronization channel used for propagation delay estimation. For example, a typical bandwidth of 1 MHz reains in the timing offset/error to be within 0.1 microsecond [23]. Consider the implementation of AirComp in a popular OFDM system, the timing offset simply introduces a phase shift to the received symbol if the offset is shorter than the cyclic prefix (CP), which can thus be corrected by sub-channel equalization. The typical CP length in LTE systems is 5 microseconds which is far longer than the typical timing offset, i.e., 0.1 microsecond [23]. Thus the time synchronization for AirComp is feasible.

**Question 3:** What is the transmission rate of AirComp?

**Answer:** The speed of AirComp is measured in terms of the computation rate, referring to the number of received functional values per channel use. Single-antenna AirComp has a unit computation rate while the rate of MIMO AirComp is multiplied by the spatial multiplexing gain.

VI. TOWARDS A NEW AIR-INTERFACE FOR 6G

While 5G is currently being deployed, research on 6G has started aiming at commercializations starting in 2030. In the 6G era, we will witness the widespread deployment of edge computing and AI, network softwarization and virtualization, and massive IoT connecting tens of billions of devices. They jointly constitute a network architecture that provides ubiquitous computing and intelligence needed by mobile applications and the solutions of large-scale problems our society faces. To meet the even more stringent requirements of mission critical
or data intensive applications than their 5G counterparts, researchers are striving to develop an extremely fast 6G air interface, which will provide tens-of-gigabit access speeds by exploiting the terahertz spectrum and reduce the network response latency to be close to one millisecond. Unfortunately, a brute-force approach faces seemingly unsurmountable obstacles, e.g., extremely short propagation ranges of terahertz transmission, and total latency reaching its physical limit with separated computation and communication. This calls for the design of a new air interface that will further enhance spectrum efficiencies and reduce latency via seamless integration of sensing, computation, control, and AI. AirComp is a technology belonging to this new paradigm. To unleash its full potential in the 6G era, besides the techniques discussed in this article, advancements in the following directions among others will be also important in our view.

- **New AirComp Protocols:** They include new signalling procedures for initiating the AirComp transmission, new pilot designs for efficient channel estimation, synchronization, and new *hybrid automatic repeat request* (HARQ) protocols customized for AirComp.

- **Coexistence Between AirComp and Communications:** It is envisioned that AirComp will coexist with the conventional communication applications in 6G. Therefore, new techniques for managing the co-channel interference between the two networks become essential. In particular, due to the simultaneous transmission from multiple devices, AirComp may introduce more severe uplink interference towards nearby BSs, as compared to the conventional communication users. This thus makes the interference management more difficult.

- **AirComp over mmWave and THz:** The 6G spectrum will include the millimeter-wave (mmWave) and terahertz (THz) bands. Their drawbacks of severe prorogation loss can be overcome by the deployment of massive MIMO. How to implement AirComp using massive MIMO over the mmWave/THz bands has to be carefully studied, by accounting for the unique channel models for these bands and the efficient hybrid beamforming architecture.

- **Large-scale AirComp:** 6G networks will be highly heterogeneous comprising different types of access points and devices associated with a wide range of services. On the other hand, 6G networks are expected to be 3D by extending the 2D terrestrial networks vertically by adding aerial nodes such as UAVs, balloons, and satellites. To fully exploit enormous data at the edge, developing large-scale AirComp for deployment over such heterogeneous and hierarchical networks is an interesting direction.

- **AirComp Performance over Practical Networks:** While theoretical studies show the promise of AirComp, the underpinning ideal assumptions such as perfect CSI may lead to much smaller gains in practice due to e.g., imperfect CSI and synchronization. Therefore, extensive system-level performance evaluation under practical settings are needed for evaluating and refining AirComp before it can become an effective technology in practice.

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