A Survey on Wireless Data Aggregation Through Over-the-Air Computation

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Abstract. In next-generation communications, it is anticipated that accommodating extremely massive access will pose challenges due to the high density of Internet-of-Things (IoT) nodes and the limited wireless resources of traditional wireless data aggregation (WDA) techniques. Unlike the conventional orthogonal multiple access methods, over-the-air computation (Aircomp) allows multiple access over the same resources through the waveform superposition property of wireless channels, thereby supporting highly efficient WDA. This paper addresses the approach of Aircomp and reviews existing research on the wireless applications facilitated by Aircomp.

Keywords: Over-the-air computation (AirComp) · wireless data aggregation (WDA) · unmanned aerial vehicle (UAV) · sensor networks · federated learning

1 Introduction

The continuous rise of Internet of Things (IoT) devices poses significant challenges in providing wireless connectivity in expansive networks, and these challenges have not been fully addressed even with advanced technologies like advanced multi-antenna techniques and new spectrum including millimeter wave (mmWave) and sub-Terahertz (sub-THz). There is a growing interest in the development of wireless data aggregation (WDA) technologies for sixth-generation (6G) communication, aiming to gather data dispersed across various devices such as sensors and mobile devices.

Conventional WDA strategies, which typically decouple communication processes from computation, grapple with constraints like limited radio resources and bandwidth limitations, thereby hindering the accommodation of massive access [1]. To remedy these issues, numerous studies are observing over-the-air computation (AirComp) as a key solution to enable effective WDA across a vast array of devices [2]. AirComp utilizes the waveform superposition characteristics of wireless channels, enabling the aggregation of vast data transmitted simultaneously by devices and facilitating low-latency WDA. Contrary to traditional methods that separate communication and computation, AirComp amalgamates these two elements to achieve its objectives. Aircomp aims to support

N.-S. Vo et al. (Eds.): INISCOM 2024, LNICST 595, pp. 181–188, 2024.
https://doi.org/10.1007/978-3-031-67357-3_13

accurate and low-latency data aggregation in next-generation IoT applications and is anticipated to handle information from various fields, with many new technologies being designed for this purpose. This paper provides an overview of the fundamental concepts of Aircomp and reviews recent research in this area. Section 2 discusses the basic mechanisms to understand Aircomp, addressing the computed nomographic functions and their processing. Section 3 investigates the applications that can be supported by Aircomp. Further, in Sect. 4, we present simulation results. Finally, the conclusion of the paper is presented.

2 Definitions of Aircomp

Through the capabilities of Aircomp, nomographic functions, which include average, geometric mean, weighted sum, polynomial, and Euclidean norm, can be computed using appropriate data pre-processing and post-processing. Depending on the target function and system characteristics, desired functions can be obtained through the necessary pre-processing and post-processing. In this section, we will examine these functions and the processing procedures of Aircomp to understand what Aircomp is.

2.1 Nomographic Functions

Assuming K sensors in an ideal multiple-access channel (MAC), we describe a method to efficiently compute functions by taking advantage of the superposition property of the wireless MAC.

$$y = \sum_{k=1}^{K} W_k, \tag{1}$$

where W_k is a transmitted signal of the sensor k, while y is the received signal at the fusion center (or receiver).

Each sensor has a measurement signal x_k and has a function value $f : \mathbf{R}^K \to \mathbf{R}$ to be extracted from the received signal.

Table 1. Representative nomographic functions

Name	Expression
Arithmetic Mean	$y = \frac{1}{K}\sum_{k=1}^{K} x_k$
Weighted Sum	$y = \sum_{k=1}^{K} w_k x_k$
Geometric Mean	$y = (\prod_{k=1}^{K} x_k)^{\frac{1}{K}}$
Polynomial	$y = \sum_{k=1}^{K} w_k {x_k}^{\beta_k}$
Euclidean Norm	$y = \sqrt{\sum_{k=1}^{K} {x_k}^2}$

Table 1 summarizes representative nomographic functions which possess the mathematical properties that AirComp can support. In [3], structured codes were designed for the computation of functions of sensing values collected by multiple sensors by analog modulation and transmission over a typical wireless MAC.

2.2 Pre-processing and Post-processing Functions

By designing appropriate pre-processing and post-processing schemes, Aircomp can realize the computation of the nomographic functions simply by the signal superposition. The above task considering the ideal MAC has a pre-processing function set $\phi_k : \mathbf{R} \rightarrow \mathbf{R}$ and a post-processing function $\psi : \mathbf{R} \rightarrow \mathbf{R}, \forall k \in 1, \cdots, K$. $\phi_k(x_k) = (\phi_k \circ x_k)$ is the pre-processing function of node k and $\psi(y) = (\psi \circ y)$ becomes the post-processing function.

Each sensor pre-processes its signal and simultaneously sends $W_k = \sum_{k=1}^{K} \phi_k(x_k)$ to the receiver. The receiver then processes the sum of the received signals as a post-processing function to obtain the desired calculation of the measurement signal f of the K sensors.

$$f(x_1, \cdots, x_K) = \psi\left(\sum_{k=1}^{K} \phi_k(x_k)\right) \tag{2}$$

The above equation can be interpreted as an evaluation of function f and indicates whether the nomographic function is related to Aircomp. Examples of this type of function can be found in [4,5]. Simultaneous transmission of Aircomp achieves low latency regardless of the number of devices and saves spectral resources, enabling fast WDA [6].

3 Aircomp Applications

Aircomp offers an integrated communication-computational design, so it can have a variety of applications in distributed sensing, federated learning, and UAV clusters. In this section, we will discuss the applications of Aircomp in various fields.

3.1 UAV-Enabled Aircomp

In reality, a large volume of data is generated on mobile devices, which can move across a wide area or even out of the service region. Such scenarios can hinder the efficient execution of Aircomp, necessitating a flexible communication system to address these challenges. Unmanned aerial vehicles (UAVs) act as versatile devices in supporting terrestrial communication networks, establishing line-of-sight (LoS) air-to-ground channels, and enhancing communication performance through mobility control [7]. Furthermore, UAV-mounted access points have the capacity to offer flexible network services to devices distributed in intricate environments and can serve as valuable devices in realizing Aircomp. In [8], the use of UAV as a Base Station is explored, where block coordinate descent and successive block approximation methods are applied to support AirComp by optimizing the UAV's trajectory and power. In [9], a system that employs AirComp with UAVs is considered to aggregate data dispersed among ground sensors across multiple slots in a vast area. In [10], research is conducted to maximize the minimum computational amount across multiple clusters by optimizing multi-UAV trajectories, cluster scheduling, etc., taking AirComp into account in a multi-cluster network.

3.2 Aircomp in Sensor Networks

In [11], a solution is provided that allows sensors to transmit consistently through the exploration of linear fitting and computational feasibility of the measurements, ensuring that the cluster head directly receives the desired function value. It also analyzes the robustness of the computed functions to channel noise, demonstrating bandwidth savings in large sensor networks. In [5], Aircomp is set up to compute the arithmetic mean of values measured by sensors for environmental monitoring by estimating the proportion of active and inactive sensors. In disaster avoidance systems, where the functional value of interest might be the maximum chemical level or temperature, Aircomp is considered in [12] for constructing thermal distributions through low-power wide-area networks. In [13] it is considered how to effectively compute the objectives of a distributed estimation problem using multiple-input multiple-output (MIMO)-AirComp and demonstrates its effectiveness for observation of data in the form of a linear combination.

3.3 Federated Learning via Aircomp

The typical procedures of machine learning (ML) with the training and inference processes are supported by centralized cloud data centers with broad accessibility. However, with the emergence of new mobile devices including unmanned aerial vehicles (UAVs) and other non-terrestrial network entities, it is also of paramount importance to guarantee security and low latency, which makes the application of cloud computing-based ML methodologies infeasible and impractical [14]. Consequently, there has been a growing body of research aimed at enabling mobile edge computing services [15]. Notably, in [16], a fast model aggregation scheme leveraging AirComp was proposed to enhance communication efficiency and accelerate the federated learning (FL) system. In [17], the authors proposed an efficient edge FL approach using analog beamforming, which reduces the computational complexity compared to existing optimization algorithms, and the implementation of this framework was demonstrated in an autonomous driving simulation platform. An algorithm based on Aircomp to facilitate local model consensus through device-to-device communication and establish the convergence of wireless decentralized FL algorithms can be found in [18].

4 Simulation Results

In this section, we numerically evaluate the mean squared error (MSE) of an AirComp system with K devices. It is assumed that the measurement information is encoded into N symbols. Also, each sensor detects data, which corresponds to a sequence length of N, enabling the retrieval of information based on the total received power [19].

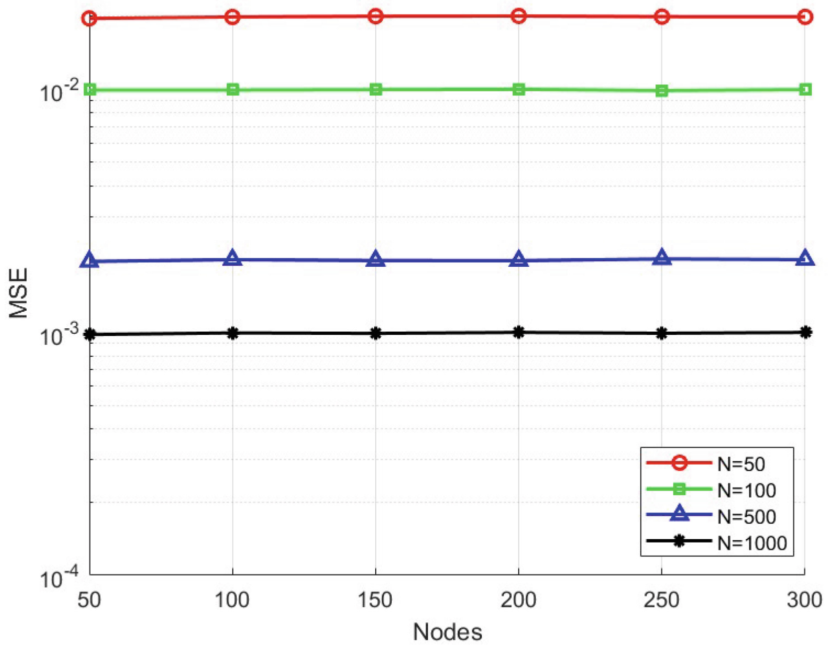

Fig. 1. The MSEs of AirComp as a function of the number of nodes and sequence length.

When h_k represents the channel coefficient from device k to the fusion center (FC) and $b_k[n]$ denotes the transmit coefficient, the received signal at the FC can be expressed as

$$y[n] = \sum_{k \in K} h_k b_k[n] s_k + w[n], \tag{3}$$

where s_k is the normalization function, and $w_k[n]$ is the additive white Gaussian noise (AWGN) with a mean of zero and a variance of σ^2. Suppose $\hat{f}$ be the estimate of f. To recover the average message, the FC applies a denoising factor denoted by η, enabling the representation of the recovered signal [20]. Consequently, the MSE can be expressed as

$$\mathtt{MSE} = \mathbb{E}\left[\left|\hat{f} - f\right|^2\right]. \tag{4}$$

To understand the structure of the AirComp system and analyze the impact of its parameters, we present simulation results of the system's MSE. We utilize a carrier frequency of 1 GHz and set the sensing data range to $[-\Delta, \Delta]$. The MSE simulations are based on 10^5 iterations. In Fig. 1, we examine the MSE variation as the number of devices, K, increases from 50 to 300, with the sequence lengths $N \in \{50, 100, 500, 1000\}$. In this simulation, the sensing data range was set to $[-1, 1]$. This analysis shows how different system parameters affect the MSEs of the system, where such impacts may vary depending on the system model configuration. Notably, in Fig. 1, it was observed that there is a decrease in the MSE with an increase in the random sequence length N.

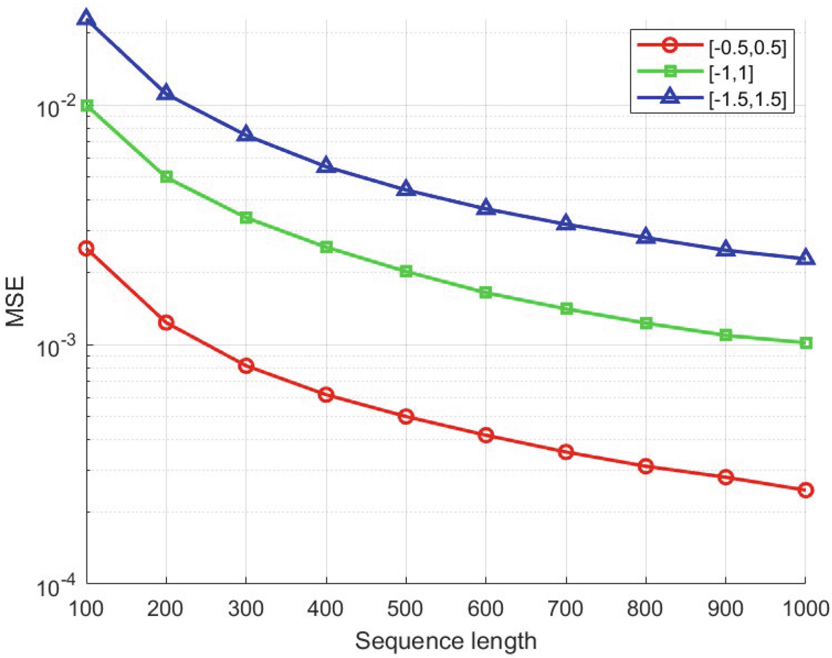

Fig. 2. The MSEs with a change of sequence length and sensing data range

In Fig. 2, we delve into the MSE performance with a fixed number of devices, $K = 100$, while changing the sequence length N. Additionally, we assume various sensing data ranges such as $[-0.5, 0.5]$, $[-1, 1]$, and $[-1.5, 1.5]$. In the figure, it is shown that an increase in N leads to a decrease in MSE, which is in line with the results in Fig. 1. Furthermore, it was observed that a smaller sensing data range results in a lower MSE.

5 Conclusion

In the era of next-generation communications, there will be the establishment of a vast network of mobile applications. With the continuous growth in the number of devices, a novel approach will be imperative to accommodate the vast connectivity. Taking advantage of the superposition property of wireless channels, AirComp can achieve enhanced spectrum efficiency and improved computation speed. As a result, this paper deviates from traditional design principles to discuss AirComp for massive IoT. Within this paper, we delve into the fundamental concepts of AirComp and review recent research that illustrates its seamless integration across various fields. Additionally, through simulation results, we investigate how each parameter affects the MSE performance of an AirComp system.

Acknowledgement. This work was supported by the MSIT, Korea, in part under the National Research Foundation of Korea grants (RS-2023-00303757, NRF-2022R1F1A1065367 and NRF-2022R1A4A3033401) and in part under the ITRC support programs (IITP-2024-2021-0-02046) and in part under the Convergence security core talent training business support program (IITP-2023-RS-2023-00266615) supervised by the IITP.

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