NEXT-GENERATION IOT NETWORKS: INTEGRATED SENSING COMMUNICATION AND COMPUTATION

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ABSTRACT

To enable the exponential expansion of Internet of Things (IoT) applications, IoT devices must gather and transmit massive amounts of data to the server for further processing. By employing the same signals for both radar sensing and data transmission, the integrated sensing and communication (ISAC) approach provides simultaneous data gathering and delivery in the physical layer. Over-the-air computation (AirComp), which leverages the analog-wave addition property in multi-access channels, is a communication method that also supports function computation. In order to leverage the individual benefits of ISAC and AirComp, this work focuses on Integrated Sensing Communication and Computation (ISCCO) framework for the IoT network. Since the IoT sensors are small size low cost devices and each is equipped with single antenna, and hence to make the processing of received echo simple this work assume that the waveform transmitted by each sensor is orthogonal to each other. Furthermore, joint optimal power allocation for each sensor in the IoT network and the combining vector at the EC is designed such that the signal-to-noise (SNR) ratio at the EC is maximized. However, the design challenge lies in the non-convex joint optimal power allocation for each IoT device and the combining vector at the server. To address this, an iterative algorithm is proposed which provides closed-form solution for each quantity in each iteration. Results show that the proposed optimal power allocation and orthogonal waveform design scheme outperforms the equal power allocation-based design.

Index Terms— Internet of Things (IoT), Integrated Sensing and Communication (ISAC), Over-the-air computation.

1. INTRODUCTION

The emerging Internet of Things (IoT) services such as smart cities, digital twins, and autonomous vehicles are expected to be enabled by the next-generation wireless networks (6G and beyond) [1]. To support the data collection required for these applications, IoT devices must gather significant data from the environment and send it to the server for processing [2]. In conventional data processing pipelines, these operations are typically carried out individually with limited mutual assistance and integration [3]. However, the integrated sensing and communication (ISAC) technique uses the same spectrum and signals for both radar sensing and data communication, enabling simultaneous data collection and delivery in the physical layer [4], and hence it has become a widely used technology. It has been applied to a range of systems such as RIS systems, vehicular networks, smart homes, edge learning systems, millimeter-wave radar, and communication networks. Despite this, the operation of computation remains isolated as it mostly occurs in the upper layers.

To increase efficiency and decrease overhead, integrating sensing, communication, and computation is a natural step. The over-the-air computation (AirComp) technique achieves function computing through simultaneous signal transmission in the physical layer using the analog-wave addition property in a multi-access channel [5, 6]. AirComp has prompted the unification of these three operations into a single signal transmission. This has led to the development of a new framework known as integrated sensing, communication, and computation over-the-air (ISCCO) [7]. A brief study of the existing works is presented next.

1.1. Existing works

There has been research focused on co-existence as well as improving radar sensing and communication performance using convex optimization techniques. Li and Petropulu [8] proposed a joint radar beamformer and communication covariance matrix design with an objective to maximize the radar sensing signal to interference plus noise ratio (SINR), while taking specific power and capacity constraints into account. To address radar interference, a communication receiver was designed in [9] to demodulate communication data while iteratively removing radar interference using a successive interference cancellation (SIC) algorithm. But these designs require information about CSI, radar probing waveforms, and communication modulation formats to be frequently exchanged between radar and communication devices for coexistence. While a control center connecting both systems via a wireless link or backhaul channel may facilitate cooperation, implementation challenges remain. In [10], an advanced co-existence scheme was proposed to reduce the overheads of exchanging side-information. A dual-functional system was designed to support both radar and communication, and the performance of both functionalities was unified based on the rate distortion theory [11].

Though the ISAC is a well-studied technology that combines sensing and communication functions, but the computation aspect is often overlooked since it falls under the upper layers. Fortunately, AirComp allows for fast function computation through physical layer transmissions. As a result, integrating the operations of sensing, communication, and computation is a natural step that can be achieved through the combination of ISAC and AirComp. Hence, in this work, we have considered an IoT network in which the sensors transmit orthogonal waveform to sense the parameter/quantity of interest and sends the communication symbol over the wireless channel to the central edge center (EC) for the receive processing. The signal transmitted by each sensor reaches as a sum at the EC over a multiple access channel. Hence, the objective is to develop an optimal transmit power allocation scheme and the received beamforming vector at the EC jointly. The joint non-convex SNR maximization problem is then solved using an iterative scheme which gives closed-form solution for the optimal power allocation and receive beamformer vectors in each iteration. The orthogonal waveform transmission from each sensor makes the sensing echo processing simpler for low cost single antenna sensor-based IoT system. Next, we dicuss the system model and problem formulation in detail.

2. SYSTEM MODEL AND PROBLEM FORMULATION

We consider an IoT system which is designed to support simultaneous sensing, communication, and computation. The M IoT sensors are assumed to be low-cost and thus single-antenna equipped. These sensors collaboratively transmit modulated signals to detect a target while passing data to a multi-antenna central edge center (EC) for data fusion in the manner of AirComp.

Let $x_m(t)$ denotes the transmit signal to be designed by the m-th sensor, and c_m represents the communication symbol to be transmitted to the EC by the m-th sensor. The transmit waveform for the mth sensor is $\tilde{x}_m(t) = c_m x_m(t)$. Furthermore, defining g_{im} be the target-related reflectivity coefficient from the m-th sensor to the i-th sensor, the receiving echo at each sensor can be modelled as

$$r_m(t) = g_{mm}\tilde{x}_m(t) + \sum_{i\neq m} g_{mi}\tilde{x}_i(t) + n_r^m(t). \quad (1)$$

The sampled version of which is given by

$$\boldsymbol{r}_m = g_{mm}c_m\boldsymbol{x}_m + \sum_{i\neq m} g_{mi}c_i\boldsymbol{x}_i + \boldsymbol{n}_r^m,$$

where $\boldsymbol{x}_m = [x_m(1),\ldots,x_m(T)]^T \in \mathbb{C}^{T\times 1}$, $\boldsymbol{r}_m = [r_m(1),\ldots,r_m(T)]^T \in \mathbb{C}^{T\times 1}$ and $\boldsymbol{n}_r^m = [n_r^m(1),\ldots,n_r^m(T)]^T \in \mathbb{C}^{T\times 1}$.

By using the matched filter at the mth sensor, one obtains

$$y_m = \boldsymbol{x}_m^H\boldsymbol{r}_m = g_{mm}c_m\boldsymbol{x}_m^H\boldsymbol{x}_m + \sum_{i\neq m} g_{mi}c_i\boldsymbol{x}_m^H\boldsymbol{x}_i + \boldsymbol{x}_m^H\boldsymbol{n}_r^m.$$

Considering the each sensor is light-weight, and only simple computation is supported. Therefore, the orthogonality is treated as a compulsory constraint as

$$\begin{cases}\boldsymbol{x}_m^H\boldsymbol{x}_i = 0 & \forall i\neq m\\ \boldsymbol{x}_m^H\boldsymbol{x}_m = p_m, & \end{cases}$$

where p_m is the transmitted power of the mth sensor.

For the over-the-air computation, by the receiving combiner, the EC aims to obtain $\sum_{m=1}^{M} c_m$. This may correspond to scenario where the objective is to an average of all the transmit information from each sensor m in the IoT. Therefore, the communication model is

$$y_c(t) = \boldsymbol{a}^H\sum_{m=1}^{M}\boldsymbol{h}_m c_m x_m(t) + \boldsymbol{a}^H\boldsymbol{n}_c(t), \quad (2)$$

where $\boldsymbol{h}_m \in \mathbb{C}^{N_c\times 1}$ is the Rayleigh flat fading channel vector from the m-th sensor to the EC which is constant over the T observation interval, $\boldsymbol{a} \in \mathbb{C}^{N_c\times 1}$ is the combiner at the EC, and $\boldsymbol{n}_c(t) \sim \mathcal{CN}(\boldsymbol{0},\sigma_n^2\boldsymbol{I}) \in \mathbb{C}^{N_c\times 1}$ is the noise vector at the EC. Moreover, the quantities N_c represents the number of the receiving antennas of the EC. By collecting all received signal together (i.e. $\boldsymbol{y}_c = [y_c(1),\ldots,y_c(T)] \in \mathbb{C}^{1\times T}$, we have

$$\boldsymbol{y}_c = \boldsymbol{a}^H\boldsymbol{HCX} + \boldsymbol{a}^H\boldsymbol{N}_c, \quad (3)$$

where $\boldsymbol{N}_c = [\boldsymbol{n}_c(1),\ldots,\boldsymbol{n}_c(T)] \in \mathbb{C}^{N_c\times T}$, $\boldsymbol{C} = \text{Diag}(\{c_m\}) \in \mathbb{C}^{M\times M}$, $\boldsymbol{H} = [\boldsymbol{h}_1,\ldots,\boldsymbol{h}_M] \in \mathbb{C}^{N_c\times M}$ and $\boldsymbol{X} = [\boldsymbol{x}(1),\ldots,\boldsymbol{x}(T)] \in \mathbb{C}^{M\times T}$. The expression for the signal-to-noise (SNR) at EC can be evaluated as

$$\begin{aligned}\text{SNR} &= \frac{\left\|\boldsymbol{a}^H\boldsymbol{HCX}\right\|_2^2}{\mathbb{E}\left[\left\|\boldsymbol{a}^H\boldsymbol{N}_c\right\|_2^2\right]} = \frac{\boldsymbol{a}^H\boldsymbol{HCXX}^H\boldsymbol{C}^H\boldsymbol{H}^H\boldsymbol{a}}{\mathbb{E}\left[\boldsymbol{a}^H\boldsymbol{N}_c\mathbf{N}_c^H\boldsymbol{a}\right]}\\ &= \frac{\boldsymbol{a}^H\boldsymbol{P}(\boldsymbol{X},\boldsymbol{p})\,\boldsymbol{a}}{\sigma_n^2\boldsymbol{a}^H\boldsymbol{a}}. \end{aligned} \quad (4)$$

We aim to maximize the SNR at the EC for the symbol estimation from communication point of view. Recall that the required orthogonality, we have

$$\boldsymbol{XX}^H = \text{Diag}(\mathbf{p}),$$

where $\mathbf{p} = [p_1, p_2, \ldots, p_M]^T \in \mathbb{R}^{M\times 1}$. Therefore, the problem is formulated as

$$\begin{aligned}\underset{\boldsymbol{a},\boldsymbol{X},\boldsymbol{p}}{\text{maximize}} \quad & \frac{\boldsymbol{a}^H\boldsymbol{P}(\boldsymbol{X},\boldsymbol{p})\,\boldsymbol{a}}{\boldsymbol{a}^H\boldsymbol{a}}\\ \text{subject to} \quad & \boldsymbol{XX}^H = \text{Diag}(\boldsymbol{p})\\ & \boldsymbol{1}^T\boldsymbol{p} \leq P_{total}\\ & \boldsymbol{p} \geq P_{min}\boldsymbol{1}, \end{aligned} \quad (5)$$

where $\boldsymbol{P}(\boldsymbol{X},\boldsymbol{p}) = \boldsymbol{H}\boldsymbol{C}\boldsymbol{X}\boldsymbol{X}^H\boldsymbol{C}^H\boldsymbol{H}^H$ and $\mathbf{1}$ is a vector of all ones of appropriate dimension. Next, in order to solve the above optimization we propose an iterative algorithm which is described next in detail.

3. PROPOSED ALGORITHM

In order to solve the optimization problem in (4), we use the alternating method. Initially, we assume that $\boldsymbol{X}$ and $\boldsymbol{p}$ are known, the sub-problem to find optimal $\boldsymbol{a}$ can be formulated as

$$\underset{\boldsymbol{a}}{\text{maximize}} \quad \frac{\boldsymbol{a}^H\boldsymbol{P}(\boldsymbol{X},\boldsymbol{p})\,\boldsymbol{a}}{\boldsymbol{a}^H\boldsymbol{a}} \tag{6}$$

which is in the form of well known Rayleigh quotient and the closed-form solution of $\boldsymbol{a}$ is the scaled eigenvector corresponding to the maximum eigenvalue of the matrix $\boldsymbol{P}(\boldsymbol{X},\boldsymbol{p})$.

Next, the sub-problem to find the optimal $\boldsymbol{X}$ and $\boldsymbol{p}$ for a given $\boldsymbol{a}$ is

$$\begin{aligned} \underset{\boldsymbol{X},\boldsymbol{p}}{\text{maximize}} \quad & \operatorname{Tr}\left(\boldsymbol{X}\boldsymbol{X}^H\boldsymbol{Q}\right) \\ & \boldsymbol{X}\boldsymbol{X}^H = \operatorname{Diag}(\boldsymbol{p}) \\ & \mathbf{1}^T\boldsymbol{p} \le P_{total} \\ & \boldsymbol{p} \ge P_{min}\mathbf{1}, \end{aligned} \tag{7}$$

where $\boldsymbol{Q} = \boldsymbol{C}^H\boldsymbol{H}^H\boldsymbol{a}\boldsymbol{a}^H\boldsymbol{H}\boldsymbol{C} \in \mathbb{C}^{m\times m}$. This problem can be recast into the one w.r.t. $\boldsymbol{p}$ given by

$$\begin{aligned} \underset{\boldsymbol{p}}{\text{maximize}} \quad & \operatorname{Tr}\left(\operatorname{Diag}(\boldsymbol{p})\,\boldsymbol{Q}\right) \\ & \mathbf{1}^T\boldsymbol{p} \le P_{total} \\ & \boldsymbol{p} \ge P_{min}\mathbf{1}. \end{aligned} \tag{8}$$

Without loss of generality, assume that the index of the largest diagonal value of $\boldsymbol{Q}$ is i, then the optimal solution is given by

$$\boldsymbol{p}^\star = \left[\underbrace{P_{min},\ldots,P_{min}}_{i-1}, P_{total} - (M-1)\,P_{min}, \underbrace{P_{min},\ldots,P_{min}}_{M-i}\right]^T. \tag{9}$$

If largest diagonal value appears more than once in the diagonal elements i.e. $\tilde{M}$, then the optimal solution is the one where the sum to these indices of the largest values is equal to $P_{total} - \left(M - \tilde{M}\right)P_{min}$ with the remaining elements being P_{min}. Given the optimal power allocation $\boldsymbol{p}^\star$, the remaining task is to construct an orthogonal matrix $\boldsymbol{X}$ such that $\boldsymbol{X}\boldsymbol{X}^H = \operatorname{Diag}(\boldsymbol{p}^\star)$. Recall that $\boldsymbol{X} = [\boldsymbol{x}_1,\ldots,\boldsymbol{x}_M]^T \in \mathbb{C}^{M\times T}$. For the guarantee of perfect orthogonality, it implies that the requirement $T \ge M$ should be satisfied. Therefore, assume that the orthogonal matrix $\boldsymbol{S} \in \mathbb{C}^{M\times T}$ is used with $\boldsymbol{S}\boldsymbol{S}^H = \boldsymbol{I}_M$, then the optimal $\boldsymbol{X}$ is $\boldsymbol{X}^\star = \operatorname{Diag}\left(\sqrt{\boldsymbol{p}^\star}\right)\boldsymbol{S}$, where the matrix $\operatorname{Diag}\left(\sqrt{\boldsymbol{p}^\star}\right) \in \mathbb{C}^{m\times m}$ represents a diagonal matrix with the square root of each of the elements of the optimal power allocation vector $\boldsymbol{p}^\star$. This procedure is repeated until either the convergence is achieved or the maximum number of iterations have achieved in the system.

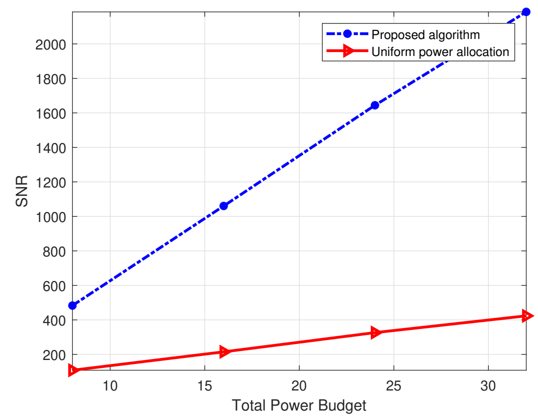

Fig. 1. SNR versus the total transmit power budget of the network.

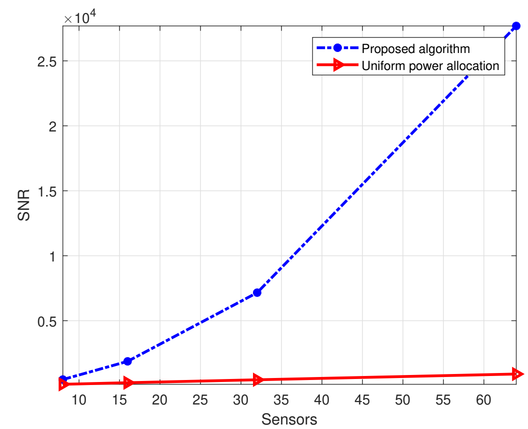

Fig. 2. SNR versus the total number of sensors in the network.

4. SIMULATION RESULTS

Unless otherwise specified, the simulation parameters are set as follows: $M = 8$ single antenna sensors, and EC with $N = 15$ antennas. All channels are assumed to be independent Rayleigh fading, modeled as independent complex Gaussian random variables with zero mean and non-identical variance. Additionally, the maximum total transmit power budget of the IoT network is set as $P_T = 10$ mW. The figures are generated by averaging over 1000 simulation realizations, each with independent channels.

Fig. 1 plots the SNR as a function of total transmit power budget of the network. As the transmit power budget increases the SNR performance increases linearly. From the performance comparison point of view we have also plotted the performance corresponding to the equal power allocation, and it can be readily deduced from the figure that our proposed optimal power allocation scheme outperforms the equal power allocation based scheme.

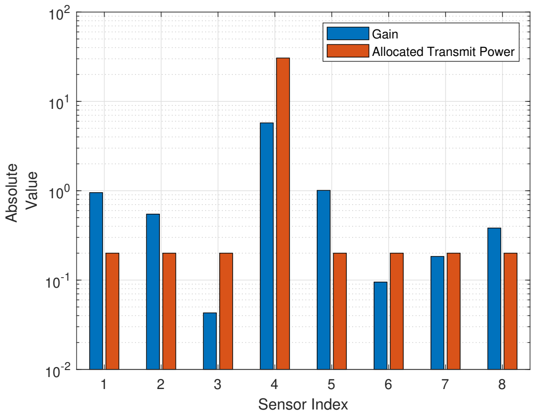

Fig. 3. Bar plot depicting the power distribution according to the channel power of each sensor.

Fig. 2 depicts the SNR performance of the proposed scheme as a function of number of sensors in the network. As expected as the number of sensors increases in the system, EC will have more and more observations available and which leads to an enhancement in the SNR. Once again, the proposed design outperforms the equal power allocation-based design.

In Fig. 3 we have plotted a bar diagram depicting the gain $\mathbf{a}^H \boldsymbol{h}_m$ for each sensor m along with the power allocated to that particular mth sensor which is denoted by p_m. As can be readily seen in the figure that the maximum power has been allotted to sensor corresponding to the maximum gain while the other sensors in the system have been allocated the minimum power denoted by p_{min}.

5. CONCLUSION

In this paper, we developed a joint ISAC and Over-the-Air framework for the improved SNR performance in a next generation IoT system by enabling simultaneous sensing and computation via Aircomp. A non-convex problem of jointly optimizing the transmit power allocation for each IoT device, together with the data aggregation beamformer at the EC has been solved using an iterative framework. The orthogonal transmit waveform by each sensor makes the proposed design simpler for an IoT network which generally consists of a low cost single antenna sensor nodes. This work contributes to the emerging research area of ISCCO and opens up several avenues for further research, such as sensor scheduling, vehicular tracking, and target surface estimation.

6. REFERENCES

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