Deployment Optimization for Meta-material Based Internet of Things

Xu Liu, Jingzhi Hu†, Hongliang Zhang‡, Boya Di†, and Lingyang Song†
†College of Engineering, Peking University, Beijing, China,
‡Department of Electronics, Peking University, Beijing, China,
Department of Electrical Engineering, Princeton University, Princeton, NJ, USA

Abstract—In this paper, we propose a Meta-IoT system to achieve ubiquitous deployment and pervasive sensing for future Internet of Things (IoT). In such a system, sensors are composed of dedicated meta-materials whose frequency response of wireless signal is sensitive to environmental conditions. Therefore, we can obtain sensing results from reflected signals through Meta-IoT devices and the energy supplies for IoT devices can be removed. Nevertheless, in the Meta-IoT system, because the positions of the Meta-IoT devices decide the interference among the reflected signals, which may make the sensing results of different positions hard to be distinguished and the estimation function should integrate the results to reconstruct 3D distribution. It is a challenge to optimize the positions of the Meta-IoT devices to ensure sensing accuracy of 3D environmental conditions. To handle this challenge, we establish a mathematical model of Meta-IoT devices’ sensing and transmission to calculate the interference between Meta-IoT devices. Then, an algorithm is proposed to jointly minimize the interference and reconstruction error by optimizing the Meta-IoT devices’ position and the estimation function. The simulation results verify that the proposed system can obtain a 3D environmental conditions’ distribution with high accuracy.

I. INTRODUCTION

In the upcoming 6G systems, Internet of Things (IoT) plays an important role in various applications, such as intelligent industrial manufacturing and environmental protection [1]. As a result, an extremely large number of IoT sensors are needed to collect sensory data of the environment, which will be approximately 10-fold more than that in 5G [2]. However, the existing sensors face challenges to support the dense deployment of IoT devices, as they need power supplies for sensing and transmission. Therefore, traditional sensors cannot continuously work without any human intervention for an ultra-long time [3]. To achieve pervasive environment sensing, it is necessary to develop sensors working without power supplies.

Fortunately, meta-material shows the potential to work as passive sensors satisfying the no-battery requirement of 6G sensing applications, which we refer to as Meta-IoT devices [4]. The Meta-IoT devices are printed circuits on supportive substrates combined with some sensitive materials and work as the passive wireless signal reflector. Therefore, their frequency response for wireless signals can be exploited to be sensitive to specific target. Compared with active wireless sensors, Meta-IoT devices are capable of simultaneous sensing and transmission and have no power supplies and maintenance, negligible volume, and ultra-low-cost.

In this paper, we consider the Meta-IoT system to obtain the 3D distribution of environmental conditions. In such a system, several Meta-IoT devices are deployed and a pair of the wireless transceiver is used to measure the reflected signals. Then, the distribution of environmental conditions is estimated by the signals reflected by Meta-IoT devices. Nevertheless, it remains a challenge to reconstruct the 3D distribution of environmental conditions by using the Meta-IoT system. This is because the Meta-IoT device worked as the passive wireless signal reflector and the reflected signals from Meta-IoT devices may interfere with each other, which makes the sensing results of different positions hard to be distinguished leading to high sensing errors through these signals.

To address this issue, we first analyze the transmission model between the transceiver. Then, according to the transmission model, we further analyze how the Meta-IoT devices’ position influences the interference among these Meta-IoT devices. In order to handle the interference among Meta-IoT devices and minimize the reconstruction error, we formulate a joint Meta-IoT devices’ position and estimation function optimization problem. As the formulated problem is NP-hard, we decompose it into two sub-problems: interference minimization problem and estimation function optimization problem, and solve them sequentially. By using numerical simulation, we verify the capability of the proposed system to reconstruct the 3D distribution of multiple environmental conditions with low error.

In the literature, several works have discussed the use of the meta-material for various types of sensing applications, such as gas concentration [4], humidity [5], strain [6] and so on. However, these works focus on the design to improve the sensing performance while the transmission is neglected. Moreover, only a single Meta-IoT is deployed in the system, which can only obtain the results of a specific area. In our system, to achieve 3D distribution of environmental conditions sensing, several Meta-IoT devices are deployed and the mutual interference in the transmission process is also considered.

The rest of this paper is organized as follows. In Section II, we present the design of the Meta-IoT device. In Section III, we introduce the Meta-IoT system and analyze the transmission model. Then, in Sections IV and V, to minimize the reconstruction error of the distribution of environmental conditions, we formulate a joint Meta-IoT devices’ positions and estimation function optimization problems and solve them,
respectively. In Section VII we demonstrate the simulation results. Finally, conclusions are drawn in Section VII.

II. M E T A - I O T D E V I C E S

In this section, we first describe the components and the structure of a Meta-IoT device unit. Then, we proposed an equivalent circuit model and establish the model of the reflection coefficient of the Meta-IoT device based on the equivalent circuit model.

A. Meta-IoT Unit

Meta-IoT devices are wireless passive devices constitute of meta-material. By designing the component meta-material to have specific structures and sensitive materials, we can make the frequency response of the Meta-IoT device sensitive to the multiple environmental conditions.

As shown in Fig. 1, the proposed Meta-IoT device unit is composed of \( N_s \) split ring resonators (SRRs). Each SRR consists of a dielectric substrate and a square metal ring which is printed on the substrate and has a gap that is filled with sensitive materials. With different sensitive materials, each SRR is designed to sense a certain environmental condition. Except for the sensitive material and the gap width, the \( N_s \) SRRs have the same structure and are composed of the same material. Therefore, we take the \( n \)-th \((n \in [1, N_s])\) SRR as an example in the following to analyze the reflection coefficient.

B. Equivalent Circuit Model

Based on [7], the SRR can be approximated by an RLC resonant circuit as illustrated in Fig. 2 (a). For the \( n \)-th SRR with gap width \( d_n \), the \( n \)-th aimed environmental condition being \( c_n \) and the other environmental conditions being \( c_{-n} \). Then, according to the circuit model given in Fig. 2 (a), the impedance can be calculated as

\[
Z_n(f, c_n, c_{-n}, d_n) = R_n + \frac{1}{2 \pi f C_{\text{surf}}(c_n, c_{-n}, d_n)} + \frac{R_{\text{en}}(c_n, c_{-n}, d_n)}{1 + 2 \pi f C_{\text{en}}(c_n, c_{-n}, d_n)}. \tag{1}
\]

where \( f \) denotes the frequency of wireless signals, \( R_n \) donates the resistance of the metal ring, \( L_n \) denotes the self-inductance, \( C_{\text{surf}} \) denotes the capacity corresponding to the surface, \( R_{\text{en}}(c_n, c_{-n}, d_n) \) denotes the resistance of the sensitive material at environmental conditions \( c_n \) and \( c_{-n} \), and \( C_{\text{en}}(d_n) \) denotes the capacity caused by the gap whose width is \( d_n \).

\[
\frac{Re(Z_n)}{|Z_n|^2} = 1 - \alpha \frac{Re(Z_n)}{|Z_n|^2}. \tag{4}
\]

Due to there are multiple SRRs involved in the Meta-IoT device unit, to distinguish the absorption peak caused by different SRRs, we need to design the different structural parameters for each SRR. As the resonance frequency increases with gap width \( d_n \), the absorption peak moves to the right when \( d_n \) increases in Fig. 2 (b). Therefore, we are able to design SRRs with different gap widths to make their absorption peak in different frequency points. Then, based on (3) and (4), the reflection coefficient of the Meta-IoT device can be expressed as

\[
S(f, d, c) = \frac{1}{N_s} \sum_{i \in [1, N_s]} s_i, \tag{5}
\]

where \( d \) donate the gap widths of \( N_s \) SRR. Besides, the reflec-
The received signal powers are influenced by the reflection coefficients of Meta-IoT devices, which are determined by the environmental conditions. Therefore, the processing unit can potentially obtain the sensing results by analyzing the received signals’ power. Moreover, the processing unit adopt an estimation function to reconstruct the distribution within a target space around the Meta-IoT device. Without loss of generality, we assume that the target space is discretized into $M$ space grids, and denote the set of $M$ space grids as $M$.

The detail of the estimation function will be discussed in Section V.

B. Transmission Model

In such a system, the Tx and Rx arrays have line-of-sight (LOS) paths to each Meta-IoT device. Without loss of generality, we take the case when the Tx array sends directional signals towards different directions, so that they can transmit polarized directional signals with bandwidth $[f_i, f_u]$ to each Meta-IoT device and receive the reflected signal.

The positions of the Tx and Rx antenna arrays can be expressed as $x_t$ and $x_r$. Besides, the $N$ Meta-IoT devices are deployed on the walls around the room, as illustrated in Fig. 3. We denote the available position set where the Meta-IoT device can be deployed as $S_X$. Here, the position of the $i$-th Meta-IoT device is denoted by the $x_i$, $(x_i \in S_A, \forall i \in [1, N])$ and the positions of the $N$ Meta-IoT devices constitute a set $X$.

As described in Section II, the Meta-IoT devices’ reflection coefficients are sensitive to the environmental conditions. To sense the distributions of environmental conditions, the Tx antenna array sends a polarized wireless signal to each device, and the Rx antenna array receives the signals reflected by the Meta-IoT device.

The received signal powers are influenced by the reflection coefficients of Meta-IoT devices, which are determined by the environmental conditions. Therefore, the processing unit can potentially obtain the sensing results by analyzing the

$$P_{R,i}(c,f) = 10 \log_{10} \left( \frac{P_f \sigma \lambda^2}{32 \pi^3 \rho^2 \frac{4 \pi}{3} i, t} \cdot S_i(c,f) G_i^t(\theta_i, \varphi_i, f) G_i^r(\theta_i, \varphi_i, f) \right) + \sum_{j \neq i} \sum_{j \in [1, N]} \left( P_{f} \sigma \lambda^2 \cdot S_j(c,f) G_j^t(\theta_j, \varphi_j, f) G_j^r(\theta_j, \varphi_j, f) \right)$$

1) Target: The first part of received power is carried by the signals that are reflected by the Meta-IoT device to be sensed.
2) Interference: The second part is due to the signals reflected by the Meta-IoT devices other than the target device.

3) Environmental reflection: The third part is the power reflected by the surrounding environment, where $R_{env}$ donates the reflection coefficient and can be obtained with the help of $|T|$, $\eta$ is the ratio of the transmitted power reflected by the environments and total transmitted power.

4) Noise: The fourth part donates the noise, i.e., $\varepsilon$, in the power measurement, which is assumed to follow a Gaussian distribution $(0, \sigma_n^2)$, with $\sigma_n$ being the variance of the measurement noise.

Besides, in (8), it can be observed that the received signal power is influenced by the $S_i(e, f)$. If $S_i(e, f)$ can be derived from the received power, the environmental conditions at the $i$-th Meta-IoT device can be estimated. Nevertheless, as can be observed in (8), suffers from the interference due to the signals reflected by other Meta-IoT devices as well as the environment scattering, which makes $S_i(e, f)$ hard to estimate. To handle this issue, we propose a novel method of deriving distribution of environmental condition from the received signals, which will be described in detail in Section IV.

C. Meta-sensing Protocol

To obtain the distribution of environmental conditions through the received signals’ power, we propose the following Meta-IoT sensing protocol to coordinate the measuring process of the $N$ Meta-IoT devices’ reflected signals at frequencies $f_1, \ldots, f_L$, where $\{f_i\}_{i=1}^L$ are a set of discretely sampled frequencies within spectrum band $[f_1, f_L]$. The protocol is described as follows.

The measuring process is carried periodically, and in each measuring period, the $N$ Meta-IoT devices are measured sequentially. Specifically, in the $i$-th measurement ($i \in [1, N]$), the Tx and Rx antenna arrays steer their main-lobes towards the $i$-th Meta-IoT device. Then, the Tx sends the wireless signals at frequencies $f_1, \ldots, f_L$, sequentially, and the Rx respective record the received signal power values. Thus, for the $i$-th device’s wireless signal, the received signal powers can be expressed by an $L$ dimensional column vector, i.e., $p_{R,i}$. For $N$ Meta-IoT devices, the received signal powers can be expressed as an $L \times N$-dimensional matrix, i.e., $P_R = [p_{R,1}, \ldots, p_{R,N}]$. We refer to $P_R$ as the measurement matrix.

At the end of each period, the obtained measurement matrix, i.e., $P_R$, is sent to the processing unit, which handles it by the estimation function and obtains the estimation of the $N_s$ environmental condition distribution in the current period.

V. PROBLEM FORMULATION

In this section, a joint position and estimation function optimization problem is formulated to reconstruct a 3D distribution of environmental conditions with minimal error.

To begin with, we first define the estimation function properly, which is used by the processing unit to estimate the distributions of the environmental conditions based on the measurement matrix, i.e., $P_R$. We have discretized the target space into $M$ space grids, and the $N_s$ environmental conditions within the $m$-th space grid is denoted by a column vector, $\tilde{c}_m$. Then, the distribution can be expressed as a matrix, i.e., $\tilde{C} = [\tilde{c}_1, \ldots, \tilde{c}_M]$. Thus, the estimation function can be expressed as a mapping from $P_R$ to $\tilde{C}$. Without loss of generality, we assume that the estimation function is a parametric function $f^w : P_R \rightarrow \tilde{C}$, with $w$ being the parameter vector.

The objective is to minimize the difference between the estimated environmental condition and the true values in the target space $M$, which we refer to as the reconstruction error. From the system model, it can observe that the reconstruction error is influenced by two factors, which are the Meta-IoT devices’ position and the estimation function of the processing unit. First, the Meta-IoT devices’ position influences the interference between each Meta-IoT device, which makes reflection coefficient, i.e., $S_i(e, f)$, hard to estimate. Then, the estimation function determines the ability of the processing unit to reduce the Meta-IoT reflection coefficient in the received signal power matrix, as well as the ability to reconstruct the distributions of the environmental conditions by using the Meta-IoT reflection coefficient.

Therefore, we need to minimize the reconstruction error by optimizing the Meta-IoT devices’ position, i.e., $X$ and the estimation function parameters, i.e., $w$. Then, the problem can be formulated as

\[
(P1) : \min_{w, X} L_{RMSE}(w, X) = \sum_{c_i \in C} ||\tilde{c}_i - c_i||^2,
\]

\[
s.t. \quad \tilde{C} = f^w(P_R), \quad X \subseteq \mathbb{S}_N,
\]

where $C$ is the set of the known distributions of environmental conditions in the $M$ space grids. $c_i$ means the environmental conditions of $i$-th space grid. Here, in (9a), $L_{RMSE}(w, X)$ denotes the sum of root mean squared error (RMSE) given parameters $w$ and $X$. Constraint (9b) indicates that the estimated environmental conditions are obtained by the transceiver using the estimation function with parameter $w$ and measurement matrix $P_R$. Besides, constraint (9c) is due to the devices’ position must be in accord with the available position set.

V. ALGORITHM DESIGN

Since the constraints are non-convex and the estimation function is non-linear, (P1) is an NP-hard problem. Besides, the function parameter $w$ is coupled with the devices’ positions, which makes problem (P1) even harder to solve.

To handle these issues, we decompose (P1) into two subproblems and propose the algorithms to solve them sequentially. First, an interference minimization problem is proposed to minimize the interference through Meta-IoT devices’ position optimization. Then, an estimation function optimization problem is aimed to minimize the reconstruction error through optimizing the estimation function.
A. Interference Minimization Problem

The purpose of the interference minimization problem is to guarantee that the mutual interference between different Meta-IoT devices is as low as possible. The optimization variables $\mathcal{X}$ are the device position parameters, i.e., $x_i$. Based on the transmission model proposed in (3), the interference comes from the second part of the received signal power. Then, we aim to minimize the max interference by maximizing the minimal ratio between the channel gains of the target signals and the interference signals.

In the measurement of the i-th Meta-IoT device, we denote the channel gain of each device reflected signal by $g_{i,j}$. Therefore, based on (3) the interference minimization problem can be formulated as:

\[
(sP2) : \max_{x^*} \min_{\mathcal{X} \in \mathcal{X}} \sum_{i=1}^{N} \frac{g_{i,i}(x_i)}{\sum_{j \neq i} g_{i,j}(x_i, x_j)}, \quad (10a)
\]

\[
\text{s.t.} \quad \eta, \quad (10b)
\]

\[
g_{i,j} = G_x^t(\theta^r_j, \varphi^r_j, f) \cdot G_x^c(\theta^t_j, \varphi^t_j, f), \quad (10c)
\]

\[
(\theta^r_j, \varphi^r_j) = H(x_j, \vec{x}_t), \quad (10d)
\]

which indicates that the signal power concentrate on only one device for each sensing action. Besides, based on geometric, the function $H$ in (10d) is able to be explicitly represented.

To solve (sP2) efficiently, we adopt the simulated annealing algorithm, which can handle large combinatorial global optimization problems and avoid falling into local optimal, so that it has a high probability of finding the global optimal $x^*$. The simulated annealing algorithm is based on the principle of changing the solving state to a worse value by probability which is decreased with iteration, so that it is capable to jump out the local optimal state. The algorithm terminates until there is no better result has been solved in several iterations or reaching the maximum number of iterations.

Specifically, based on the $S_X$ in (10b), the constraint of $(\theta^r_j, \varphi^r_j)$ and $(\theta^t_j, \varphi^t_j)$ can be calculated with the function $H$. Then, $(\theta^r_j, \varphi^r_j)$ is optimized by the simulated annealing algorithm. Besides, we denote the resulting optimized Meta-IoT position set as $\mathcal{X}^*$, which will be used in the next estimation function optimization problem.

B. Estimation Function Optimization Problem

After solving the (10a), the parameters $\mathcal{X}$ in (2a) can be regarded as the constant and we adopt the optimized Meta-IoT position set, i.e. $\mathcal{X}^*$. Then, the optimization variables are the estimation function parameters, i.e., $w$, and the estimation function optimization problem can be formulated as:

\[
(sP3) : \min_w L_{RMSE}(w, \mathcal{X}^*), \quad \text{s.t.} \quad \eta \quad (11)
\]

To solve (sP3), we model that $f^*$ as a deconvolution neural network, which is an efficient model for mapping low-dimensional features to higher-dimensional features with de-convolution layers [13]. The neural network consists of a fully-connection layer, a deconvolution layer and two convolution layers, and uses the measurement matrix as input to calculate $\mathcal{C}$. In this case, the parameter vector of the estimation function stands for the weights and the biases of each layer.

Then, to obtain the optimal parameter vector, i.e., $w^*$, the training data set, i.e., $D_{train}$, is needed. The training data set is generated by a set of random simulated received power matrix based on the simulate reflection coefficient with specifically $d^*$, i.e., $S(f, d^*, c)$, the known distributions of environmental condition, i.e, $C$ and the optimal Meta-IoT position set, i.e., $\mathcal{X}^*$, in the simulation environment.

After that, we optimize $f^*$ by training it on $D_{train}$ using the supervised learning algorithm. The training of $w$ is performed by iteratively updating $w$ along the negative gradient of the RMSE loss in (11), i.e.,

\[
w = w - \beta \nabla w L_{RMSE}(w, \mathcal{X}^*),
\]

where the gradient $\nabla w L_{RMSE}(w, \mathcal{X}^*)$ is calculated by using the back-propagation algorithm and $\beta$ denotes the learning rate which used to control the updating rate.

Sum up the algorithms to solve sub-problem (sP2) and (sP3), and we can summarize the complete algorithm to solve (P1) as Algorithm 1.

Algorithm 1 Algorithm to solve Meta-IoT system optimization.

Input: $S_X$ (available position set), $S(f, d^*, c)$ (the simulate reflection coefficient with specifically $d^*$), $C$ (known distribution of environmental condition), $\eta$, $R_{env}$, $N$;

Output: $\mathcal{X}^*$, $f^*$;

1: Solve the (sP2) and obtain the optimal Meta-IoT position set $\mathcal{X}^*$ by using the simulated annealing algorithm.

2: Based on $C$, $\mathcal{X}^*$ and $S(f, d^*, c)$, generate the training data set $D_{train}$.

3: Based on $\mathcal{X}^*$, and $D_{train}$ to train the neural network by solving (sP3), and obtain the optimized estimation function $f^*$.

4: return $\mathcal{X}^*$, $f^*$

VI. SIMULATION RESULTS

In this section, to validate the effectiveness of the proposed Meta-IoT system, we design and implement a Meta-IoT system to sense the temperature and humidity levels for in an indoor environment and present the simulation result. We first provide simulation results of the proposed system. Besides, we give insight into how the Meta-IoT devices’ positions and quantity influence the system’s precision.
In the simulation, Meta-IoT device consists of two SRRs. The first SRRs has temperature-sensitive material within its gap and is aimed for sensing temperature, which we refer to as the TSRR. Similarly, the second SRR contains humidity-sensitive material for sensing humidity and is referred to as HSRR. More specifically, the Meta-IoT is made of copper rings and FR-4 supportive substrate. The temperature-sensitive material is the polymer used in NTC thermistor and the humidity-sensitive material is the powder used in the hygrometer. The Meta-IoT device’s design is guided by the reflection coefficient model, which has proposed in Section II and the gap widths is chosen as \( d^* \). Besides, the reflection coefficient, i.e., \( S(f, d^*, c) \), is simulated with the help of CST software [9].

Besides, we denote the target space is a rectangular space and the Meta-IoT devices can be deployed on the wall. The transceivers are placed in the middle of space and the antenna array is composed with \( 4 \times 4 \) omnidirectional antennas. The detail simulation parameters are presented in Table I.

Fig. 4 shows the comparison between the reality distribution and the estimation distribution for the testing temperature distribution by solving (P1). The test distribution is similar with the distributions, which are used to generate train set. Besides, in both figures, the red triangle represents the position of the transceivers and the blue dots represent the position of Meta-IoT devices, which has been optimized with (sP2). It can observe that the temperature gradient has been captured by the estimation function and the mean reconstruction error is less than 2.9°C.

Fig. 5 shows the different resulting RMSE by solve (sP3) under different Meta-IoT position-case. The first case indicates the resulting RMSE for the estimation function given the optimal position set, i.e., \( X^* \), obtain by solve (sP2), and the second case indicates the resulting RMSE with random position set. Besides, there are five different distributions of temperature and humidity, and each of which has 256 generated datas to construct the training set, i.e., \( D_{train} \). It can be observed that the resulting RMSE values of different Meta-IoT position sets decrease as the number of deployed Meta-IoT device increase. Besides, the optimal Meta-IoT position lead to the lowest RMSE under different number of device, which means the system can reach higher precision with the help of position optimization to minimize the interference.

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