Geo-indistinguishable Mechanisms for Spatial Crowdsourcing via Multi-Objective Evolutionary Optimization

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Abstract—Industrial Internet of Things (IIoT) has exploded key revolutions in several leading industries, such as energy, agriculture, mining, transportation, and healthcare. Due to the nature of high capacity and fast transmission speed, 5G plays a pivotal role in enhancing the industrial procedures, practices and guidelines, such as crowdsourcing, cloud outsourcing and platform subcontracting. Spatial crowdsourcing (SC)-servers (such as offered by DiDi, MeiTuan and Uber) assign different tasks based on workers’ location information. However, SC-servers are often untrustworthy and have the threat of revealing workers’ privacy. In this paper, we introduce a framework Geo-MOEA (Multi-Objective Evolutionary Algorithm) to protect location privacy of workers involved on SC platform in 5G environment. We propose an adaptive regionalized obfuscation mechanism with inference error bounds based on geo-indistinguishability (a strong notion of differential privacy), which is suitable for the context of large-scale location data and task allocations. This offers locally generated pseudo-locations of workers to be reported instead of their actual locations. Further, to optimize the trade-off between SC service availability and privacy protection, we utilize MOEA to improve the global applicability of the mechanism in 5G environment. Finally, by simulating the location scenario, the visual results on experiments show that the mechanism can not only protect location privacy, but also achieve high availability of services as desired.

Index Terms—5G, Industrial Internet of Things, Differential privacy, Multi-objective optimization.

I. INTRODUCTION

In recent years, the rapid development of 5th Generation (5G) technology and Industrial Internet of Things (IIoT) has promoted the development of digital world, smart cities, smart society construction and new industrial procedures. Ubiquitous information service is an important feature of the 5G and IIoT-enabled smart cities. 5G terminals with low delay, high speed and large throughput become gradually the main channel for people to experience high quality services. In particular, spatial crowdsourcing (SC) [1] based on location services has led to an exponential growth in data collection and sharing of intelligent terminals. In SC, a larger number of tasks are requested and allocated at the SC-server among a wider range of potential workers for providing faster and efficient services. However, when an SC-server assigns a task, the location of workers is likely to be disclosed. In recent years, many privacy protection techniques and technologies appear to protect workers’ location information [2]. However, the existing solutions still have several limitations, which are summarized as follows. (1) Relying on trusted third-party entities. Most of the current mechanisms utilize centralized differential privacy, which requests a third-party trusted entity to collect workers’ actual locations. To et al. [3] introduced a trusted Cellular Service Provider (CSP) to partition the domain of worker locations. Indeed, CSP has also the risk of being invaded, which destroys individual sensitive information. (2) Ignoring adversary’s inference attack. Some obfuscation mechanisms generate pseudo-locations with Local Differential Privacy (LDP) guarantee via geo-indistinguishability [4], while not resisting against the Bayesian inference attack by prior knowledge. (3) Single-objective optimization. Generally, current privacy mechanisms adopt single-objective optimization [5]. In fact, we have to take into account the trade-off between the conflicting metrics, privacy level and service quality. and (4) Small-scale location domain and task allocation. Current LDP protection mechanisms [6] mainly adopt the linear programming methods to improve the allocation efficiency that result in much higher computational complexity, while a previous scheme DPIVE [7] can only be applied separately in small-scale disjoint domains.

To address aforesaid issues, we propose and develop an adaptive obfuscation mechanism called ‘Geo-MOEA’ (Multi-Objective Evolutionary Algorithm) based on geo-indistinguishability, that achieves the distortion privacy guarantee on each worker location. Under our privacy framework, workers report their pseudo-locations directly to the server without the need of any trusted third-party entity. The mechanism involving expected distortion errors can effectively resist attacks via prior knowledge. Moreover, the obfuscation scheme employs the genetic operator to optimize the two conflicting metrics, expected inference error and service quality loss, for producing multiple optimized recommendations.

The main contributions are as follows:

- For the SC task allocation scenario of large-scale location domain, we propose an adaptive obfuscation mechanism named ‘Geo-MOEA’ based on geo-indistinguishability offering workers with personalized LDP protection, and achieving the protection of distortion privacy in all regions to defeat Bayesian inference attacks.
- We introduce a mechanism combining location differential privacy and MOEA to simultaneously optimize the conflicting metrics that achieves the optimal balance
between reducing service quality loss and preserving average expected inference error.

- The results obtained from a series of experiments we conducted show that our proposal is more effective than the existing recommendation mechanisms. Providing multiple recommendation mechanisms for practical applications can reduce workers’ travel distance while protecting workers’ location privacy in a global and scalable sense.

II. RELATED WORK

We review related works in the direction of classical and differential privacy protection methods as well as multi-objective optimization.

Classical privacy protection methods. With the rapid development of 5G and IIoT, Spatial Crowdsourcing (SC) becomes more and more popular while the arising location privacy problem has also attracted extensive attention. For this, traditional privacy protection methods mainly include spatial anonymity and cryptography. Specifically, spatial anonymity technology often uses a spatial anonymity area to replace the user’s accurate location information. As a common kind of spatial anonymity models in SC, k-anonymity is first proposed by Sweeney [8]. This model requires that each of the released locations be indistinguishable from at least k − 1 other locations. It has the fatal weakness that k-anonymity is vulnerable to attacks of background knowledge and reference [9]. Homomorphic encryption is a good model to ensure the confidentiality of task’s location policy [10] while it has disadvantages of large key size and low calculation efficiency. Hence, it is not practical for large-scale scenarios [11].

Differential privacy protection. The Differential Privacy (DP) method is a strong privacy concept [12] that has been widely used for location privacy protection recently. In particular, To et al. [3] develop DP based Private Space Decomposition (PSD) to protect location privacy. Gong et al. [13] protect workers’ location and reputation privacy by using reputation-based DP method. Both schemes rely on a trusted third-party entity to protect location privacy and some adversary attacks may lead to the disclosure of true locations.

Geo-indistinguishability and expected inference error. Local Differential Privacy (LDP) can help users to report their pseudo-locations. Based on geo-indistinguishability [14], some LDP frameworks are proposed for SC scenario [4], [5]. Expected inference error [15] is a concept of distortion privacy complementary to geo-indistinguishability, and can provide strict privacy protection against Bayesian attacks. Shokri [6] combines both concepts to construct the Joint mechanism and optimizes utility using linear programming. Yu et al. [16] formally study their relationship and combine them by adding personalized error lower bounds. Later, DPIVE mechanism is presented and solves the previous privacy theory problem of intersections among protection location sets [7]. Recently, Liu et al. [17] propose an obfuscation mechanism with the Gamma distribution and use a game-theoretic approach to maximize two-users’ utilities while preserving desired location privacy radius. However, these works focus mainly on the optimization of utility and have no concern with global trade-off between the conflicting utility and distortion privacy.

Multi-objective optimization. With the rapid development of scientific and engineering areas, a variety of optimization problems containing multiple conflicting objectives have appeared [18]. This means that there does not exist a single solution optimizing all of the objectives. It is natural to find the Pareto optimal set that contains multiple solutions trading off between all of the objectives, where the improvement of one objective cannot be achieved without the deterioration of some other objectives. A number of MOEAs [19] have been proposed to search for well-converged solutions by using conventional reproduction operators [20], such as the genetic algorithm [21] and Particle Swarm Optimization (PSO) [22]. To achieve better privacy protection and higher service quality, Zhang et al. [23] provide a PSO anonymization method to accelerate the process of finding similar attributes. However, in many occasions the convergence of the canonical PSO is premature and it suffers from local minima [24]. Zhang et al. [25] present a MOEA framework to protect private information based on the hybrid elite selection strategy. In order to obtain optimal task allocation with the differential-and-distortion geo-obfuscation, Wang et al. [5] use linear scaling to execute optimization of two concordant objectives. In this paper, for the large-scale SC data scenario, the MOEA method is adopted to realize the trade-off between the conflicting differential-and-distortion privacy and service quality.

III. SYSTEM MODEL, GOAL AND ADVERSARY MODEL

This section presents our system model, goal and properties to be achieved through our proposal, and an adversary model.

A. Spatial Crowdsourcing Model

Spatial Crowdsourcing (SC) [1] is a new type of platform for efficient and scalable data collection of online crowdsourcing in the era of mobile Internet and sharing economy, which requires the worker to travel to a specific location to complete the task. Usually, there are two categories of task assignment modes based on how workers are matched to tasks, Worker Selected Tasks (WST) and Server Assigned Tasks (SAT).

We attempt to combine the advantages of both models. The SAT model is used to assign tasks for efficient running performance, while still protecting users’ location privacy. Requesters submit tasks that include locations, online workers send their pseudo-locations to the server that assigns tasks to nearby workers.

B. Goal - Achieving Differential Privacy

Differential privacy provides provable privacy protection for users [12]. Regardless of the adversary’s prior knowledge, it ensures that any adversary can not determine the presence of a particular individual from the processed data set.

Definition 1 (Sensitivity [26]). Let D, D′ be neighboring datasets in a universe D that differ on one element. The sensitivity of function \( q : D \to \mathbb{R}^d \), given by
\[ \Delta q = \max_{D, D' \in D} \|q(D) - q(D')\|_1, \]

means the \(L_1\) norm of the maximal change on the output of \(q\) when altering any record to \(D \in D\).

For functions whose output space is non-numeric, the exponential mechanism is widely used to achieve DP.

**Definition 2** (Exponential Mechanism \([27]\)). Given a scoring function \(q : D \times R \rightarrow \mathbb{R}\) with \(R\) representing the collection of output range of a query function, the exponential mechanism \(\mathcal{M}(D, q)\) outputs \(r \in R\) with probability proportional to \(\exp \left(\frac{q(D, r)}{\Delta q} \right)\).

**Definition 3** (Geo-indistinguishability \([14]\)). Suppose that a location obfuscation mechanism satisfies, for any locations \(x, y \in \mathcal{X}\) and their Euclidean distance \(d(x, y)\),
\[
\frac{f(x'|x)}{f(x'|y)} \leq e^{\epsilon_d(x,y)}, \quad x' \in \mathcal{X},
\]
then the mechanism achieves \(\epsilon_g\)-geo-indistinguishability.

This means that two geographically close locations have similar probability distributions, which theoretically achieves that they are indistinguishable to each other for the adversary. Here, \(\epsilon_g\) represents the geo-indistinguishability parameter that is determined by the privacy budget and the circular region usually centered at the user’s location. All locations in the region have similar release distribution, which theoretically achieves \(-\text{geo-indistinguishability}\).

**Definition 4** (-DP on PLS \([16]\)). A randomized location obfuscation mechanism \(f(\cdot|x)\) achieves \(-\text{differential privacy}\) on protection location set \(\Phi\), if for any locations \(x, y \in \Phi\) and any output \(x' \in \mathcal{X}\), we have
\[
\frac{f(x'|x)}{f(x'|y)} \leq e^{\epsilon}.
\]

**C. Multi-Objective Optimization**

The definition of Multi-Objective Optimization (MOO) problems is mathematically given by
\[
\min f(x) = (f_1(x), f_2(x), \cdots, f_m(x)),
\]
where \(x = (x_1, x_2, \cdots, x_d)\) denotes the \(d\)-dimensional decision vector of a solution from decision space \(\Omega\), and \(f(x)\) is a vector containing \(m\) conflicting functions \([18], [20]\).

**Definition 5** (Pareto Dominance). For any two solutions \(x\) and \(y\), if \(f_i(x) \leq f_i(y)\) for all \(i = 1, 2, \cdots, m\) and \(f_i(x) < f_i(y)\) for at least one \(i\), then \(x\) Pareto dominates \(y\).

**Definition 6** (Pareto Optimality). A solution \(x\) is Pareto optimal, if there does not exist any solution \(y\) dominating \(x\) in the decision space \(\Omega\).

Obviously, all Pareto optimal solutions obtained are non-dominated with each other. In the current SC scenario, we will mainly consider two conflicting factors, service quality loss and expected inference error by using MOEA.

**D. Problem Statement**

With the application of 5G intelligent terminals, location-based SC services are spreading to a number of cities. The rapid growth of service data brings two serious challenges. Firstly, task allocation is often oriented to large-scale user location privacy data (such as DiDi, MeiTuan and Uber). The existing LDP protection mechanism (without a trusted third party) can not meet the large-scale location data protection \([6]\). Conventional grid methods using centralized differential privacy leads to strict boundaries between regions and affect the quality loss of task matching. It is desired to develop a framework with LDP protection to avoid the partition boundaries during task allocations. In detail, a region partition method for generating families of protection location sets is necessary for achieving LDP based on geo-indistinguishability and implement distortion privacy against attacks from adversaries with background knowledge. Secondly, most of existing privacy mechanisms ignore the balance between privacy protection and practical quality. Currently, there is no standard optimization of conflicting metrics in a global sense when users have personalized requirements of distortion privacy \([5]\, [7]\). This motivates us to combine differential location privacy and MOEA to achieve the optimal trade-off between service quality loss and average expected inference error globally in SC.

**E. Bayesian Adversary Model**

As all the location-based service (LBS) providers require the access permission to users’ location data, the location privacy is potentially disclosed to untrusted entities. Knowing user’s locations, an adversary can perform a broad spectrum of attacks. Thus, ensuring location privacy is foremost for LBS applications. A common method is location perturbation, which generates a pseudo-location based on the true location and the user sends it to the server. Following \([16], [28]\), we suppose that the discretized location set \(\mathcal{X}\) represents the user’s possible locations. An obfuscation mechanism takes the user’s real location \(x\) from \(A\) as input and randomly chooses a pseudo-location \(x'\) from \(O\) with the probability \(f(x'|x)\):
\[
f(x'|x) = \Pr(O = x'|A = x), \quad x, x' \in \mathcal{X}.\]

In general, the objective of obfuscation mechanisms is mainly to design suitable probability distribution \(f(\cdot|x)\). Similar to \([16], [29]\), we assume that the adversary has prior knowledge about user’s location, which is regarded as background knowledge to perform inference attacks. The adversary collects background knowledge by building a prior probability distribution \(\pi\) on \(\mathcal{X}\). The prior probability \(\pi\) can be obtained via population density, historical locations and so on. The adversary is also informed of the obfuscation mechanism \(f\). In the current scenario, the adversary infers the user’s real
location \( x \) under the Bayesian adversary model. After the user reports her/his pseudo-location \( x' \in \mathcal{X} \), the adversary computes the probability that each apriori location \( x \in \mathcal{X} \) is the true location in the condition of generating \( x' \), i.e., the posterior probability distribution \( \Pr(x|x') \), by

\[
\Pr(x|x') = \frac{\Pr(x, x')}{\Pr(x')} = \frac{\pi(x)f(x'|x)}{\sum_{x \in \mathcal{X}} \pi(x)f(x'|x)}. \tag{6}
\]

Afterwards, a Bayesian adversary can launch optimal inference attack to get the estimated location \( \hat{x} \) which has the minimal expected distortion, i.e.,

\[
\hat{x} = \arg\min_{y \in \mathcal{X}} \sum_{x \in \mathcal{X}} \Pr(x|x')d(y, x). \tag{7}
\]

Now we come to the conflicting metrics. The privacy level is measured by unconditional expected inference error \([15]\).

\[
ExpErr = \sum_{x' \in \mathcal{X}} \min_{x \in \mathcal{X}} \sum_{x \in \mathcal{X}} \pi(x)f(x'|x)d(\hat{x}, x). \tag{8}
\]

The service quality loss is defined by the unconditional expected distance between true and perturbed locations \([6]\).

\[
QLoss = \sum_{x \in \mathcal{X}} \sum_{x' \in \mathcal{X}} \pi(x)f(x'|x)d(\hat{x}, x). \tag{9}
\]

IV. OUR PROPOSED APPROACH

This section describes our privacy protection approach Geo-MOEA, including basic framework, domain partition, local adaptive obfuscation mechanism, MOEA and task matching.

A. Proposed Framework

We consider the privacy protection problem of SC worker locations in the SAT mode. Fig. 1 describes our proposed system framework that consists of three parts: SC-server, requesters and workers. Each worker downloads obfuscation model, generates pseudo-location and sends the false location information to SC-server. Requesters submits tasks and exposed location information to SC-Server. After receiving a task request, the SC-server determines the allocation by querying the locations reported by workers and initiates the geocast process. The SC-server is assumed to be semi-honest and intentionally deduces sensitive information of locations from the workers. It also plays the role of communications, and computations to determine task allocations are carried out at the SC-server part. Possible disclosure of worker location and identity after his/her consent to the task is outside our scope. As shown in Fig. 1, the proposed framework consists of the following steps.

- **Step 1** Domain Partition: The SC service domain is divided into \( 2^s \) cells for some integer \( s \) where each cell \( X_i \) has almost the same count of locations. The binary partition method is carried out iteratively according to the widthwise and lengthwise directions (the longer distance is preferred). This ensures that each cell obtained covers a required amount of locations and their convexity and compactness are satisfied.

- **Step 2** Local Adaptive Obfuscation Mechanism: Each worker downloads at the 5G terminal the obfuscation model of the generation matrix from the server side, and inputs preferred privacy parameter values to initialize PLS partitions. Each PLS is restricted in one \( X_i \) and meets the lower bound of inference error and geo-indistinguishability. For each PLS, the mechanism adaptively generates a reporting range \( \mathcal{Y}_i \) composed of multiple connected PLSs, with which several cells \( X_i \)’s may be associated. Such partitions are repeated randomly at each MOEA iteration.

- **Step 3** MOEA: At each iteration the obfuscation mechanism utilizes genetic evolution to generate a new partition family and improves the Pareto optimal solutions (graph). After achieving the convergence of graph’s HV value, the MOEA outputs the set of Pareto optimal recommendations. The worker selects one solution and inputs his/her actual location, which generates, by the exponential mechanism, a pseudo-location to be reported to SC-server.

- **Step 4** Task Matching: According to the collected pseudo-locations, the SC platform informs the three nearest idle workers around the task location. Finally, the task is assigned to the earliest responder.

Such a privacy framework supports Geo-MOEA to provide workers with personalized LDP protection based on geo-indistinguishability, and distortion privacy protection guarantee in all regions against Bayesian inference attacks. In particular, we develop a binary partition method adaptively producing cells, provide obfuscation mechanisms with locally adaptive reporting ranges and construct a novel multi-objective genetic algorithm with crossovers and mutations of PLS partitions.

B. Domain Partition

SC provides services generally in urban areas, and especially on the plain the main roads naturally divide the city into rectangular regions. Following this, we develop a binary partition method adaptively dividing the SC domain into multiple regions \( X_i \) with equal number of locations. Since the set of the workers’ possible locations is public, just like the distribution of bus stations, the domain can be decomposed without noise.

First, we circumscribe the domain with a rectangle according to the longitude and latitude spans. The added domain

![Fig. 1: The framework of Geo-MOEA.](image-url)
is naturally empty for locations. Next, the rectangle is divided into multiple rectangles $X_i$ by binary partitions. At each iteration, each rectangle is divided, along the larger edges, into two smaller rectangles including equal number of locations. The recursive partitions end until each cell achieves the expected range of location number. Each final cell is denoted by the region $X_i$. Different from the existing spatial decompositions [30], such a partition method takes into account the distribution characteristics of urban roads and ensures the convexity and compactness of locations in each cell.

To be specific, assume that the total number of workers is $N$ and the range of expected number of locations in each cell is $[n_0, 2n_0]$. The number of partitions is $\lfloor \log_2 \frac{N}{n_0} \rfloor$. Fig. 2 shows the three levels of partitioning $N = 400$ locations with $n_0 = 33$. In the first level, since the rectangular length is larger than its width, it divides into two rectangles, one left and the other right, equally covering 200 locations. The deeper partitions are processed recursively, which results in 8 cells.

C. Local Adaptive Obfuscation Mechanism

This section is the core part of Geo-MOEA, offering the initialization of obfuscation schemes involving adaptive reporting ranges. The flowchart is shown as PART 1 of Fig. 3.

Geo-indistinguishability and expected inference error are verified to be complementary privacy notions [16]. Given the user-defined threshold, $\text{ExpErr}(x') \geq E_m$, for the optimal inference attack using any observed pseudo-location $x'$, where the conditional expected inference error is defined as

$$\text{ExpErr}(x') = \min_{\hat{x} \in X} \sum_{x \in X} \Pr(x|x')d(\hat{x}, x), \text{ for } x' \in X.$$ (10)

Assume that the adversary narrows possible guesses to the range of PLS that includes the user’s true location. Define

$$E'(\Phi) = \min_{\hat{x} \in X} \sum_{x \in X} \frac{\pi(x)}{\pi(y)}d(\hat{x}, x).$$ (11)

Then the local lower bound for $\text{ExpErr}(x')$ is achieved as

$$\text{ExpErr}(x') \geq e^{-\epsilon}E'(\Phi).$$ (12)

This yields a sufficient condition to satisfy the threshold $E_m$.

**Theorem 1** (17). Assume that a location obfuscation mechanism satisfies the $\epsilon$-differential privacy on each PLS $\Phi$. For the optimal inference attack using any observed pseudo-location $x'$, we have $\text{ExpErr}(x') \geq E_m$, if

$$E'(\Phi) \geq e^{\epsilon}E_m.$$ (13)

In the PART 1, based on the condition (13), we first execute QK-means algorithm from [17] on each cell $X_i$ to find the optimal number $k_i$ of disjointed PLSs included. Then we randomly select $k_i$ or $k_i-1$ centers to make centralized clustering within each cell $X_i$ in ascending order of distance. Any cluster is suspended after achieving (13). When all clusters satisfy (13), the remaining points join the nearest cluster with maintaining (13). Each cluster obtained is regarded as a potential PLS. Any two PLSs do not intersect with each other. Each PLS is involved in only one cell $X_i$ and meets the threshold $E_m$. The mechanism repeats such PLS partitions to initialize a population of $n$ solutions over $X$ ($n$ PLS partitions).

For each PLS $\Phi_j$ in a partition, the mechanism constructs a reporting range $\lambda_j$ by adding the nearest PLS to $\Phi_j$ recursively according to their centers’ distance, until that at least two PLSs are included and the number of locations is not less than 50. In this way, each reporting range $\lambda_j$ is not simply the involved cell $X_i$, but sometimes intersects with several cells.

However, such initialized solutions are not optimal in general for the tradeoff of privacy level and service quality. Step 3 is required for further optimization.

D. MOEA and Task Matching

This section introduces the multi-objective genetic algorithm into optimizing the PLS partition population and generates a pseudo-location for task matching. Specifically, our innovated random combinations and variations of cluster centers in each cell lead to the crossovers and mutations of PLS partitions, respectively, which expands largely the solution space of the privacy problem.

The mechanism aims to generate higher unconditional expected inference error (ExpErr) and smaller service quality loss (QLoss) that conflict with each other. Following the line of MOEA, we describe the Pareto sets with regarding QLoss and minus ExpErr as two objective functions and use the unary Hypervolume (HV) indicator to measure the convergence and diversity of solutions. HV [20] is a usual performance metric for MOO problems that is the only unary indicator strictly monotonic with Pareto dominance. In our setting, we first find the reference point $Q$ whose coordinates are defined as the maximum values of two objectives for each Pareto-dominated solution set, respectively. Then the HV value is defined as the
area of the rectangular region surrounded by point $Q$ and each point in Pareto-dominated solution set with subtracting the overlapped area. Generally, two objective functions in MOO prefer larger values, or both smaller, which is conducive to optimization. Hence, we replace ExpErr by its opposite.

The PART 2 in Fig. 3 shows the genetic evolution of PLS partition populations. After calculating the two metrics for each population, the mechanism makes fast non-dominated ranking for each population and determines the crowded degree in each level. This generates $n$ solutions sorted by levels. Then, based on $n/2$ parents (in the PLS partition family) obtained by a binary tournament selection operator [19], the mechanism adopts crossover and mutation operators to generate $n/2$ offsprings, respectively. For crossover we randomly select $k_i$ or $k_i - 1$ cluster centers from $5$ parents in each cell $X_i$ to generate a new partition, while randomly replacing half cluster centers in each cell for mutation. Afterwards, all $2n$ solutions join the new fast non-dominated ranking and half are filtered out. Such a MOEA using genetic algorithm proceeds recursively until the maximum iteration times is attained or the increase value $\Delta HV$ vanishes.

Given the set of Pareto optimal recommendations, the worker selects a preferred solution with personalized threshold and carry out the exponential mechanism to produce a pseudo-location that is reported to SC-server. For each true location $x \in \Phi_j$, the utility (scoring) of output $x' \in \mathcal{Y}_j$ can be defined as $u(x, x') = -d(x, x')$. The sensitivity of $u$ for each PLS $\Phi_j$ is the diameter of $\Phi_j$ [7].

After a worker uploads the pseudo-location, the server improves the worker’s information. Once a task request is received, the server geocasts the task to the three idle workers closest to the task according to the collected pseudo-locations, see the right part of Fig. 2. The worker who approves first is qualified to execute the task. The task and the worker may be really located in different cells $X_i$ and even are far away from each other with a small probability. The metrics of worker travel distance (WTD) denoting their actual distance measures the service availability to a certain extent.

Theoretically similar to [7], the mechanism satisfies the $\epsilon$-differential privacy on each PLS $\Phi_i$. Moreover, for any two locations from different PLSs whose reporting ranges $\mathcal{Y}_j$’s intersect with each other, Geo-MOEA preserves weak differential privacy with a deviation factor on the coefficient as follows.

**Theorem 2.** Assume that disjoint PLSs, $\Phi_i$ and $\Phi_j (i \neq j)$ have the reporting range $\mathcal{Y}_i$ and $\mathcal{Y}_j$, respectively, then the exponential mechanism $\mathcal{K}$ satisfies \( \left( \frac{D(\mathcal{Y}_j)}{D(\Phi_j)} + \frac{D(\mathcal{Y}_i)}{D(\Phi_i)} \right) \frac{3}{2} \) differential privacy between $\Phi_i$ and $\Phi_j$. For any $x \in \Phi_i$, $y \in \Phi_j$ and $x' \in \mathcal{Y}_i \cap \mathcal{Y}_j$, we have

\[
\frac{f(x'|x)}{f(x'|y)} \leq \frac{|\mathcal{Y}_j|}{|\mathcal{Y}_i|} \exp \left( \frac{\epsilon}{2} \left( \frac{D(\mathcal{Y}_j)}{D(\Phi_j)} + \frac{D(\mathcal{Y}_i)}{D(\Phi_i)} \right) \right). \tag{14}
\]

Proof.

\[
f(x'|x) = \exp \left( -\frac{\epsilon}{D(\Phi_j)} \frac{D(\mathcal{Y}_j)}{D(\Phi_j)} \right) \sum_{t \in \mathcal{Y}_j} \exp \left( -\frac{\epsilon}{D(\Phi_j)} d(y, t) \right)
\]

\[
= \sum_{s \in \mathcal{Y}_i} \exp \left( -\frac{\epsilon}{D(\Phi_j)} \frac{D(\mathcal{Y}_i)}{D(\Phi_i)} \right) \frac{D(\mathcal{Y}_j)}{D(\Phi_j)} \exp \left( -\frac{\epsilon}{D(\Phi_j)} d(y, t) \right)
\]

\[
= \sum_{s \in \mathcal{Y}_i} \exp \left( -\frac{\epsilon}{D(\Phi_j)} \frac{D(\mathcal{Y}_i)}{D(\Phi_i)} \right) \frac{D(\mathcal{Y}_j)}{D(\Phi_j)} \sum_{t \in \mathcal{Y}_j} \exp \left( -\frac{\epsilon}{D(\Phi_j)} d(y, t) \right)
\]

The new result obtained above for variable reporting ranges provides important theoretical support on the differential privacy protection guarantee in the large-scale data scenario.

V. EXPERIMENTAL RESULTS AND EVALUATION

This section compares our Geo-MOEA approach with some previous mechanisms on the metrics of location privacy and service quality, then presents Pareto analysis, application analysis and visualization analysis. The results show that our mechanisms greatly improves service availability on the basis of ensuring individual location privacy.

A. Experimental Methodology

**Datasets.** Since SC services are mainly located in urban domains, we investigate its distribution characteristics in cities and simulate two location datasets of SC workers in a fixed domain, where one includes 200 locations (shortly, L-200), and the other 400 locations (L-400). Both datasets involve relatively dense and sparse regions. Fig. 4 presents their distribution charts with binary partitions. In each chart, all cells $X_i$ are marked in different colors. We simulate a prior distribution uniformly in which each value is sampled randomly and uniformly in $[0.0040, 0.0060]$ and $[0.0015, 0.0035]$ with normalization, respectively, on both datasets.

**Parameter settings.** The minimum expected number of locations in each cell is $n_0 = 33$. Geo-MOEA gives two privacy control knobs: 1) differential privacy parameter $\epsilon \in$
\begin{itemize}
\item {\(0.10, 0.20, \ldots, 1.50\)} and 2) threshold of expected inference error {\(E_m \in \{0.050, 0.075, \ldots, 0.300\}\). Its maximum iteration times is 500. We sample randomly 200 task locations in each dataset and average their WTDs. On comparisons of the metrics WTD, for the Pareto solutions of Geo-MOEA, only the solution with the smallest QLoss is taken into account.

B. Privacy Protection Goals

The privacy protection goals of the experiments for applications are as follows. (1) preserving \(\epsilon\)-DP inside each PLS based on geo-indistinguishability and weak DP in the large-scale data scenario. (2) achieving the lower bound \(E_m\) against the Bayesian inference attack even on isolated locations, and (3) improving the data utility for applications.

We want to mention that our proposed Geo-MOEA is able to defeat Bayesian adversary model locally and globally. Locally, the lower error threshold \(E_m\) controls the (conditional) expected inference error \(\text{ExpErr}\) for each location involving the isolated regions. In the global sense, the unconditional expected inference error \(\text{ExpErr}\) quantifies the degree of resistance to Bayesian inference attack, which provides a method to pick a solution from the Pareto optimal recommendations.

C. Pareto Analysis

In this section, we compare Geo-MOEA with DPIVE mechanism \(\square\) and PSO algorithm, especially to verify the efficiency in balancing service quality loss and average expected inference error as well as some extreme solutions. Since the lower bound \(E_m\) ensures the conditional expected inference error locally, we pay more attention to the global performance on the metrics, QLoss, Minus ExpErr, and HV.

The DPIVE carried out in each cell \(X_i\) separately is a single-objective optimization algorithm that aims to minimize the quality loss while ensuring the lower bound \(E_m\) of inference error. PSO is an evolutionary algorithm with transforming multi-objective optimization into single-objective optimization problems. In the current scenario, PSO constructs a fitness function combining both objectives to optimize the obfuscation recommendation. The fitness function formula is, \(F(\alpha) = \alpha \cdot \text{QLoss} + (1 - \alpha) \cdot \text{ExpErr}\), where \(\alpha \in \{0.0, 0.1, \ldots, 1.0\}\).

Fig. \(\square\) presents a series of comparisons on the conflicting metrics of QLoss and ExpErr with the convergent Pareto dominance solutions. Each DPIVE solution is obviously dominated by some solutions of Geo-MOEA in the (a)-(i) settings. On the aspect of QLoss, DPIVE increases by 3.6% on average and particularly 5.8% in case (c), compared to Geo-MOEA. The reasons include that, the reporting range of DPIVE is restricted in local small-scale cell while more PLSs are located in the corners, and DPIVE minimizes the average diameter of PLSs for optimizing QLoss while ignoring the fitness of ExpErr. Moreover, the Pareto solutions of Geo-MOEA are basically located at the lower left side of PSO solutions, which means that Geo-MOEA solutions can well Pareto dominate PSO’s globally. Indeed, the PSO algorithm also initializes its population, but lacks the crossover and mutation processes that help Geo-MOEA expand the solution space. As a result, the HV of Geo-MOEA solutions is twice as large as that of PSO solutions on average and even 3.3 times in case (i), which is shown in Fig. \(\square\). In a word, Geo-MOEA brings more optimized solutions, faster convergence and greater diversity while achieving the privacy protection goals.

D. Application Analysis

The distance WTD that the worker travels from the actual location to the allocated task determines the efficiency of mechanism application. We conduct comparative experiments on the two datasets with varying privacy parameter \(\epsilon\). Under each parameter setting, we average the WTDs on random tasks for comparisons of four schemes. The notation Non-privacy means Geo-MOEA without privacy protection, that is, the SC-server geocasts the three idle workers closest to the task directly based on the real locations and their average WTD is referred to.

Fig. \(\square\) shows that, compared with Geo-MOEA, DPIVE has an average increase of 2.8% and 4.3%, and a maximum
increase of 6.1% and 6.6%, respectively on the two datasets, while PSO has an average increase of 15.8% and 25.9% and a maximum increase of 28.8% and 30.1%, respectively. Geo-MOEA performs multi-objective genetic algorithms that globally saves the quality losses. On the other hand, the privacy protection for Geo-MOEA leads to more quality loss due to the spare distribution of idle workers. The algorithms produce relatively higher WTDs on the L-400 dataset because of more isolated regions involved. This shows that our mechanism can well protect the privacy of workers and improve the availability of existing SC mechanisms in the large-scale domain scenario.

E. Visualization Analysis

We make visualization analysis on the experiments under 110 settings of privacy knobs, \(E_m = 0.050, 0.075, \ldots, 0.300\) and \(\epsilon = 0.1, 0.2, \ldots, 1.0\) for each dataset. We adopt surface fitting by the metric \(H\) and mark the surface in variable colors by fitting on the metric \(WTD\). As shown in Fig. 7 for fixed \(E_m\), the larger \(\epsilon\) leads to higher \(H\) and the more expanded solution space while leading to smaller \(WTD\) naturally due to the lower level of privacy requirement. For both datasets, the metrics \(H\) and \(WTD\) reach respective extreme values at the case of \(E_m = 0.05, \epsilon = 1\). The surfaces are marked in green in the middle part around \(\epsilon = 0.6\) and more green part are expressed for \(L-400\) dataset due to its denser property.

VI. CONCLUSION

This paper implements the geo-indistinguishable location privacy protection of SC workers in 5G-enabled smart cities. Our proposed Geo-MOEA achieves to generate each pseudo-location among an adaptive reporting range at the 5G terminal with distortion privacy guarantee in the large-scale data domain. Together with a binary partition method, a multi-objective genetic algorithm for PLS partitions is introduced into the LDP protection, which realizes the optimized tradeoff between quality loss and inference error. Experimental results confirm strongly that Geo-MOEA improves data utility and applicability of the existing SC obfuscation schemes. In our future work, we plan to explore multi-task assignment problems with LDP that involves much higher computational complexity and stricter requirements on communication environments.

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