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A Spatio-temporal incentive scheme with consumer demand awareness for participatory sensing

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ABSTRACT

Participatory sensing involves smartphone users contributing data to form a body of knowledge. This paper first develops the concept of quality of contribution and consumption in the spatio-temporal sense for participatory sensing. Recognising that a significant issue which determines the success of participatory sensing is the incentive for contributors, we propose a spatio-temporal incentive (STI) scheme with consumer demand awareness. The STI scheme considers the spatio-temporal relevance between contributors and consumers and incentivizes contributors to contribute according to consumer demand. Only spatio-temporal relevant contributors for enquiry-based consumption and a subset of contributors which provide sufficient sensing coverage for coverage-based consumption are remunerated, which lead to a targeted and economical incentive scheme. Following the STI scheme, contributors and consumers determine their participation levels to maximize their utilities, and a resulting market equilibrium can be achieved, where the optimal contribution level and the optimal consumption rate, respectively, are employed. A closed form expression for the quality of consumption at the market equilibrium is derived. The performance of the STI scheme is investigated through extensive simulations, which show that good quality of consumption and sensing coverage can be experienced by consumers.

1. Introduction

Advances in wireless communication technologies and recent developments in smartphones have enabled the paradigm of participatory sensing [1–4], which is the process of individuals and communities collecting and sharing sensor information through smartphones or other portable sensors. Participatory sensing is attractive for sensing modalities associated with sensors on a smartphone such as location (GPS), light, sound and acceleration at places where people with smartphones go to in their daily lives, e.g. roads, pedestrian walkways, shopping malls etc. As smartphone users are ubiquitous and mobile, participatory sensing can provide an enlarged sensing coverage compared to conventional deployed sensor networks [5,6].

A significant issue which determines the success of a participatory sensing scheme is the incentive for contributors. Contributors could be unwilling to contribute sensor information due to the cost in terms of mobile data charges, battery lifetime and personal inconvenience [7]. The performance of the existing participatory sensing applications, such as the WeatherLah [8] and Mana Rapid Transit [9], is typically poor due to the small number and sparse and sporadic distribution of contributors.

In order to incentivize participatory sensing, several schemes have been proposed [10–12]. Typically, an incentive scheme consists of identifying the appropriate set of contributors and making payments to them accordingly. There are several criteria based on which contributors can be selected [13–15].

In the formulation of participatory sensing considered in this paper, a consumer may make a consumption that utilizes either the spatio-temporal neighboring contributions (we call this an *enquiry-based* consumption), or those in the entire sensing coverage region (we call this a *coverage-based* consumption), or both. For example, in the case of smoke haze, users may query either the air quality at a certain location, which is based on the air quality measurements in the surrounding area of the enquiry point, or the haze index, which is based on the average air quality information over the sensing coverage region. To the best of our knowledge, there is no existing work on an incentive scheme which considers both the spatio-temporal relevance between contributions and consumptions and the sensing coverage.

The main contributions of this paper are as follows. Firstly, we model the spatio-temporal relevance between contributors and consumers, and develop the concept of quality of contribution

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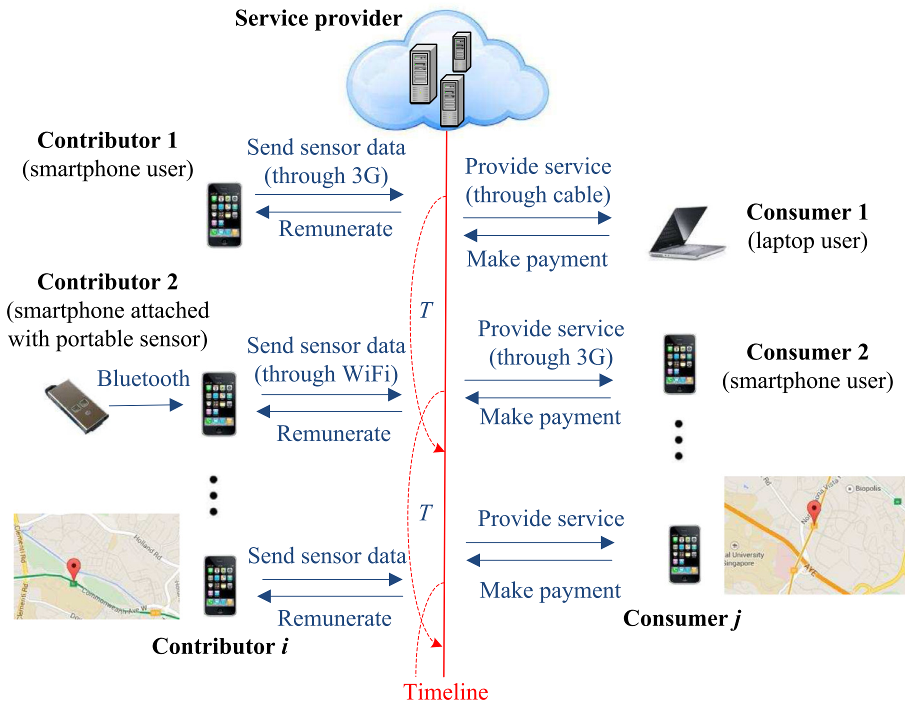

Fig. 1. The architecture of the participatory sensing system considered in this paper.

and consumption in the spatio-temporal sense for participatory sensing. Secondly, we propose a spatio-temporal incentive (STI) scheme which incentivizes the contributors according to the spatio-temporal demand of the consumptions, which results in a market equilibrium where contributors and consumers choose their optimal participation levels. A closed form expression for the quality of consumption at the market equilibrium is derived. Thirdly, we conduct performance evaluation through extensive simulations and show that the STI scheme improves the performance of participatory sensing in terms of consumer satisfaction and sensing coverage.

The rest of the paper is organized as follows. Section 2 describes the system model and then formulates the participatory sensing problem considered in this paper. Section 3 introduces the concepts of quality of contribution and quality of consumption. Section 4 provides details on various aspects of the STI scheme. How the participation levels of contributors and consumers are optimized at the market equilibrium are shown in Section 5. Section 6 investigates the performance of the STI scheme and several issues are discussed in Section 7. Section 8 reviews some related work. Finally, Section 9 concludes this paper.

2. System model and problem description

2.1. System model

Fig. 1 illustrates the architecture of the participatory sensing system considered in this paper. It consists of multiple contributors, a single service provider and multiple consumers.

- Contributors perform sensing and send the sensor information to the service provider. In return, contributors receive an amount of monetary units or credits.
- The service provider collects sensor information from contributors, processes it and provides an information service to consumers.
- Consumers query the service provider for sensing information and make payments to the service provider.

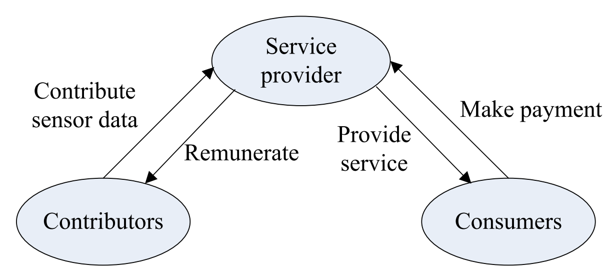

Fig. 2. The three entities in the participatory sensing system considered in this paper.

As shown in Fig. 1, contributors can be users of devices such as smartphones which are integrated with or connected to various sensors. Consumers can be users of any client device such as a laptop, smartphone or tablet. The three entities, i.e., contributors, service provider and consumers, interact with each other and attempt to maximize their own utility functions. Fig. 2 is a simplified version of Fig. 1, which shows the underlying relationships between the three entities.

2.1.1. Contributor

Contributor i performs sensing and sends the sensor information to the service provider. In return, it receives an amount of remuneration R_i from the service provider per unit time. R_i is determined by an incentive scheme, which will be described in Section 4. The utility for contributor i is the remuneration R_i minus the cost, i.e.,

$$u_z(i) = R_i - c_i q_i \eta_i \tag{1}$$

where the last term $c_i q_i \eta_i$ of Eq. (1) represents the sensing cost in unit time, c_i is a quality-dependent sensing cost[1] for each instance

[1] Quality-dependent sensing cost is a model that has been adopted in the literature by several researchers, e.g. [16,17]. The reasoning is that the higher the quality of information of the sensed information, e.g. more accurate or timely, the higher

of sensing, q_i is the quality of contribution (which will be defined in Section 3.1) and η_i is the contribution rate of contributor i.

For notational convenience, we define the *contribution level* as $b_i \triangleq q_i \eta_i$. Contributor i needs to determine b_i to maximize its utility. Hence, we rewrite Eq. (1) as

$$u_z(i) = R_i - c_i b_i. \tag{2}$$

2.1.2. Consumer

Consumer j queries the service provider for information and makes a payment to the service provider for services that are not free. Thus, the utility for consumer j is the benefit from the consumption minus the payment for the consumption. As the utility to the consumer does not always accumulate in an additive manner, we use a logarithm term to capture the fact that the increase in the utility from accumulated information slows down[2]. The utility function for consumer j is

$$u_s(j) = \beta \log\left(1 + \mu_j\right) Q_j - \mu_j r_j, \tag{3}$$

where β is a scaling factor and Q_j is the quality of consumption for consumer j, which will be defined in the next section. r_j is the fixed price charged for each instance of consumption by consumer j and μ_j is the consumption rate of consumer j.

2.1.3. Service provider

The service provider offers a platform for contributors and consumers to exchange sensor information. It can also be a processing center for raw sensor data from contributors which are processed before being provided to the consumers. In return for this service, the service provider charges a fraction of the revenue that it receives from the consumers as a commission and pays the remainder of the revenue to the contributors. Thus, the utility for the service provider u_{sp} is a fraction υ of the revenue received from the consumers:

$$u_{sp} = \upsilon \sum_{j=1}^{N_s} r_j \mu_j \tag{4}$$

where N_s is the number of consumers[3], and r_j and μ_j are as defined above.

2.2. Problem description

2.2.1. Spatio-temporal relevance between contributors and consumers

Contributor i makes a series of contributions over time. Denote z_i^t as the contribution made by contributor i at time t, which has coverage in both space and time dimensions. We assume that z_i^t is only effective within the volume of $B\left(z_i^t, T, D\right)$, where $B\left(z_i^t, T, D\right)$ is an open cylinder centered at z_i^t with temporal radius T and spatial radius D. Fig. 3 shows the spatio-temporal contribution volume of contribution $z1$. Consumer j makes a series of consumptions over time. Let s_j^t be the consumption by consumer j at time t.

Definition 1. Spatio-temporal relevance: A consumption s_j^t is spatio-temporally relevant to a contribution z_i^t when s_j^t is within $B\left(z_i^t, T, D\right)$.

As can be seen from Fig. 3, consumption $s1$ is spatio-temporally relevant to $z1$, while $s2$ is irrelevant. Let $\Phi_s\left(z_i^t\right)$ be the set of spatio-temporal consumers of contributor i. Conversely, we denote the set of spatio-temporal relevant contributors of consumer j as $\Phi_z\left(s_j^t\right)$.

the cost that is likely to have been incurred to obtain it, e.g. higher quality sensors, more computation, more energy consumed in sensing etc.

[2] A similar logarithm term is used to represent the decreasing slope of the utility from more sensing in [11] and [12].

[3] Specifically, these are enquiry-based consumers, as will be explained shortly.

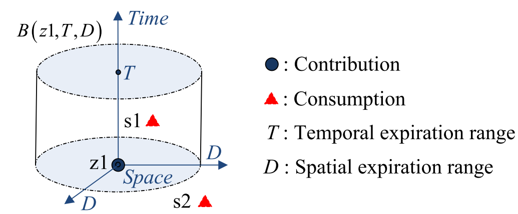

Fig. 3. The spatio-temporal contribution volume of contributor *z1*, where *s1* and *s2* represent consumer 1 and consumer 2, respectively.

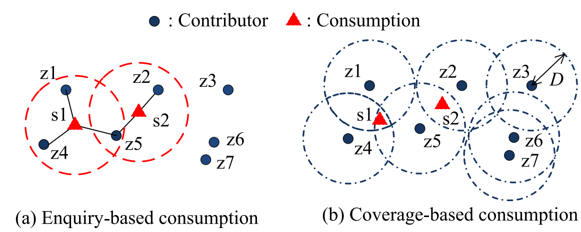

Fig. 4. An example of enquiry-based consumption versus coverage-based consumption with similar contributor deployment scenario.

2.2.2. Enquiry-based and coverage-based consumption

Depending on the proximity of the relevant contributors, a consumer can select one or both types of consumption:

- *Enquiry-based consumption*: the consumption is based on the local sensor information from the spatio-temporal relevant contributors of a particular consumer, e.g., the air quality measurements around a specific location. This type of consumption is only possible when one or more spatio-temporal relevant contributors to the consumer exist.
- *Coverage-based consumption*: the consumption is based on the aggregated sensor information from contributions all over the application area, e.g., the average air quality information over the sensing coverage region. This type of consumption has the same value for every consumer in the sensing coverage region and is possible as long as there is at least one contribution in the region.

Fig. 4 shows an example of enquiry-based consumption versus coverage-based consumption with the same contributor deployment scenario. As can be seen, an enquiry-based consumption $s1$ is based only on contributors $\{z1, z4, z5\}$ in Fig. 4(a), while a coverage-based consumption is based on all the non-overlapping contributions in the application area in Fig. 4(b). Consumer j queries the service provider for either enquiry-based consumption or coverage-based consumption, or both. Coverage-based consumption can be considered as a general service which is free-of-charge for consumers. Enquiry-based consumption can be considered as a premium service that is demanded by specific consumers, who are required to pay for this.

2.2.3. Problem formulation

Contributors and consumers determine their own participation level, i.e., contribution level b_i and consumption rate μ_j, respectively, to maximize their own utilities, given the incentive scheme. The service provider implements an incentive scheme to incentivize the contributors according to the spatio-temporal distribution of the consumer demand, in an attempt to maximize the utility of the service provider. For example, in Fig. 4, for enquiry-based consumption, contributors $\{z1, z4, z5\}$ need to be incentivized for consumption $s1$. On the other hand, for coverage-based consumption, contributors $\{z1, z2, z3, z4, z5, z7\}$ contribute to the sensing coverage with different contributions and $z6$ is not necessary, i.e. sensing coverage minus the overlapping sensing areas.

Table 1
Notations and terms used in this paper.

z_i^t	Contribution made by contributor i at time t
s_j^t	Consumption made by consumer j at time t
$B(z_i^t, T, D)$	Volume of z_i^t with temporal radius T and spatial radius D
u_z, u_s, u_{sp}	Utility of contributor, consumer and service provider
R_i	Remuneration that contributor i receives
b_i	Contribution level of contributor i
c_i	Cost of each instance of sensor data for contributor i
q_i	Quality of contribution of contributor i
r_j	Price for each instance consumption for consumer j
$w_{i,j}$	Spatio-temporal weghting factor between contributor i and consumer j
Q, Q^e, Q^c	Quality of consumption, Quality of enquiry-based consumption, Quality of coverage-based consumption
$\Phi_z(s_j^t)$	Contributor set that is spatio-temporally relevant to s_j^t
$\Phi_s(z_j^t)$	Consumer set that is spatio-temporally relevant to z_j^t
$\beta, \theta, \xi, \kappa, \upsilon, \omega, \zeta$	Weighting and scaling factors
$A(z_i^t)$	Effective coverage area of contributor i
n_s, n_z	Average number of consumers/contributors which are spatio-temporally relevant to a contributor/consumer
N_s, N_c	Total number of consumers, coverage-based contributors

In order to incentivize contributions to maximize the consumer satisfaction, there are three questions of interest:

- What is the quality of consumption Q_j in Eq. (3) considering both the enquiry-based consumption and the coverage-based consumption?
- How much does the service provider remunerate contributor i, i.e. R_i in Eq. (2), so that the consumer demand can be maximized?
- According to the proposed incentive scheme, will the system converge to a market equilibrium where all the entities maximize their utility functions?

We will answer the aforementioned questions in the following three sections. We first define the quality of contribution and consumption. Then, we design the incentive scheme to adjust the contribution level according to the consumer demand. Finally, based on the proposed incentive scheme, we determine the participation level for contributors and consumers to maximize their utilities.

For analytical simplicity, we divide the time axis into review periods, and formulate the utility functions of the three entities presented above in each review period. The notations and terms used in this paper are summarized in Table 1.

3. Quality of contribution and consumption

In order to quantify the satisfaction level of the consumption, we define the concepts of *quality of contribution* and *quality of consumption* considering both enquiry-based consumption and coverage-based consumption.

In this paper, we extend the definition of quality of contributed service (QCS) proposed in [11] to include the spatial locality aspect in addition to the original temporal aspect in order to arrive at the quality of consumption metric.

3.1. Quality of contribution

The quality of contribution measures the accuracy or certainty of contributed sensor information depending on the measurements. Reddy et al. [18] defined the quality of contribution by basing it on a discrete trust model. In this paper, we leverage the Bayesian-based belief model to define the quality of contribution. Firstly, we define *belief* as the posteriori probability of the sensor state e_k at time index k given the sensor measurements $g_1, g_2, \ldots, g_k$, i.e., $p(e_k|g_1, g_2, ., g_k)$. e_k is the ground truth of the environmental parameter at a specific location at time index k. Then, the quality of contribution is defined as the certainty of the belief

$$q_k = -\det(\mathrm{cov}(p(e_k|g_1, g_2, ., g_k))), \tag{5}$$

where $\det(\cdot)$ is the determinant and $\mathrm{cov}(\cdot)$ is the covariance.

Using Bayesian inference theory, we have

$$\begin{aligned} p(e_k|g_1, \ldots, g_k) &= \frac{p(g_k|e_k)p(e_k|g_1, \ldots, g_{k-1})}{p(g_k|g_1, \ldots, g_{k-1})} \\ &= \frac{p(g_k|e_k)\int p(e_k|e_{k-1})p(e_{k-1}|g_1, \ldots, g_{k-1})de_{k-1}}{\int p(g_k|g_1, \ldots, g_{k-1}, e_k)p(e_k|g_1, \ldots, g_{k-1})de_k} \\ &= \theta\, p(g_k|e_k)\int p(e_k|e_{k-1})p(e_{k-1}|g_1, \ldots, g_{k-1})de_{k-1} \end{aligned}$$

where $p\big(e_k|e_{k-1}\big)$ is the process model and $p(g_k|e_k)$ is the measurement model. Thus, the belief $p(e_k|g_1, \ldots, g_k)$ can be updated recursively from the last belief $p\big(e_{k-1}|g_1, \ldots, g_{k-1}\big)$. The measurement noise and process noise can be obtained from the sensor manuals and the belief can be updated using a Kalman filter. For the rest of this paper, we use q_i to represent the quality of contribution for contributor i.

3.2. Quality of consumption

Building on the utility function for a consumer (see Eq. (3)), let us consider the general form of the quality of consumption which has both the enquiry-based consumption and coverage-based consumption aspects. Hence, the quality of consumption for consumer j can be expressed as

$$Q_j = \xi \cdot Q_j^e + (1-\xi) \cdot Q_j^c \tag{6}$$

where ξ is a weighting factor, Q_j^e is the quality of enquiry-based consumption and Q_j^c is the quality of coverage-based consumption[4], for consumer j. For example, $\xi = 0$ when only coverage-based consumption is required. Note that Q_j^c has the same value for all the coverage-based consumptions (henceforth, denote as Q^c) in the sensing coverage region, while Q_j^e will vary for different enquiry-based consumptions.

3.2.1. Quality of enquiry-based consumption

The quality of enquiry-based consumption for consumption s_j^t, i.e., $Q^e\left(s_j^t\right)$[5], relies on the quality of its spatio-temporal relevant

[4] The expressions for these two quantities will be developed in the next two subsections.

[5] We use this notation to refer to the quality of enquiry-based consumption of a specific consumption s_j^t.

contributions and the spatio-temporal weighting between these contributions and the consumption of interest.

The spatio-temporal weighting between consumption j and each of its spatio-temporal relevant contributors captures the spatio-temporal decaying influence of each contribution on this consumption. It is a normalized decay factor, defined as

$$w_{i,j}(t) = \frac{e^{-\alpha\Delta t_{i,j}-(1-\alpha)\Delta d_{i,j}} - e^{-\alpha T-(1-\alpha)D}}{1 - e^{-\alpha T-(1-\alpha)D}}, \quad (7)$$

where $\Delta t_{i,j}$ is the time interval between contribution i and consumption j, $\Delta d_{i,j}$ is the spatial distance between contributor i and consumer j and α is the weighting between the temporal and spatial components of the spatio-temporal relevance. As can be seen from Eq. (7), the weighting factor is 1 at contribution z_i^t and decreases exponentially to zero at the boundary of $B\left(z_i^t, T, D\right)$. If the consumption falls outside the volume $B\left(z_i^t, T, D\right)$, it does not utilize this contribution.

Hence, the quality of enquiry-based consumption $Q^e\left(s_j^t\right)$ is the product of the quality of contribution q_i of its neighboring contributions $z_i^t \in \Phi_z\left(s_j^t\right)$ and the spatio-temporal weighting between these contributions and the consumption of interest

$$Q^e\left(s_j^t\right) = \sum_{z_i^t \in \Phi_z\left(s_j^t\right)} w_{i,j}(t) q_i \quad (8)$$

We arrive at the quality of consumption for consumer j which is the expectation of $Q^e\left(s_j^t\right)$ over a review period, i.e.,

$$Q_j^e = \mathbb{E}\left[Q^e\left(s_j^t\right)\right]. \quad (9)$$

3.2.2. Quality of coverage-based consumption

The quality of coverage-based consumption is determined by the sensing coverage of the contributions and the quality of these contributions. Here, the sensing coverage refers to the region in the application area that has an acceptable sensing contribution level.

Thus, the sensing coverage is calculated by the summation of the coverage of all the coverage-based contributors:

$$Q^c = \kappa \sum_{i=1}^{N_c} A\left(z_i^t\right) q_i \quad (10)$$

where κ is a scaling factor, N_c is the number of coverage-based contributors and $A\left(z_i^t\right)$ is the coverage area of coverage-based contributor i minus the sensing coverage which is already covered by the other contributors. In other words, $A\left(z_i^t\right)$ is the actual contribution coverage of contributor i.

4. Spatio-temporal incentive (STI) scheme

In participatory sensing, an incentive scheme can be based on the remuneration received by contributors equal to or higher than the cost of the sensing task. In this section, we develop a spatio-temporal incentive (STI) scheme to encourage contributions according to the consumption demand. There are two parts of the STI scheme, one for enquiry-based consumption and another for coverage-based consumption.

4.1. Incentive for enquiry-based consumption

For an enquiry-based consumption, its spatio-temporal relevant contributors would receive remuneration from this consumption. As mentioned earlier, an enquiry-based consumption can be viewed as a premium service for which consumers are required to make a payment. A fraction ω is deducted to remunerate contributors to coverage-based consumption (see below) and another fraction υ is deducted for the service provider. Thus, the enquiry-based contributors would receive a fraction of $(1-\upsilon-\omega)$ of the total remuneration received from its spatio-temporal relevant consumers.

The amount of remuneration a contributor receives from one of its spatio-temporal relevant consumers is proportional to the ratio of the contribution level of this specific contributor to those of all the contributions that this consumer receives. Furthermore, the total remuneration that a contributor receives is the sum of all the remunerations from its neighboring consumers $s_j^t \in \Phi_s\left(z_i^t\right)$.

Hence, the remuneration of contributor i for an enquiry-based consumption is

$$R_i = (1-\upsilon-\omega) \sum_{s_j^t \in \Phi_s\left(z_i^t\right)} \frac{b_i}{b_i + \Sigma_{-i,j}} r_j \mu_j \quad (11)$$

where $\Sigma_{-i,j}$ are the contributions made by the neighboring contributors to consumer j, r_j is the payment made by consumer j and μ_j is the consumption rate of consumer j.

As can be seen from Eq. (11), a contributor receives remuneration from all its spatio-temporal relevant consumers $s_j^t \in \Phi_s\left(z_i^t\right)$ proportional to its contribution ratio. For example, in Fig. 4(a), $z5$ receives remuneration from consumers $s1$ and $s2$. The remuneration from $s1$ is proportional to the ratio of the contribution level of $z5$ to the sum of the contribution levels $z1$, $z4$ and $z5$ received by $s1$.

4.2. Incentive for coverage-based consumption

Next, we describe how to incentivize contributors to provide sufficient sensing coverage for coverage-based consumption.

4.2.1. Selection of coverage-based contributors

The aim is to incentivize a subset of the contributors to provide sufficient sensing coverage with the minimum number of contributors. The selection of coverage-based contributors is a typical set cover problem, which is proved to be an NP-hard problem [19]. In this paper, contributors are selected for coverage-based consumption using the hardcore scheme in the Matern point process [20].

A *Matern point process* is a non-independent thinning of the Poisson point process such that the distance between any two nodes in the Matern thinning is larger than a range R [20,21]. In particular, each point of the original Poisson point process Φ_0 is attributed an independent mark uniformly distributed in the interval [0,1]. A specific node i of Φ_0 is selected in Matern point process Φ_m when the hardcore value assigned to node i is smaller than that of other points within a distance of R from node i in Φ_0. In this paper, we employ the hardcore scheme in the Matern point process in the context of participatory sensing to select the contributors which are at least a distance of $2D$ from one another. Each contributor i submits its quality of contribution q_i and the cost for this contribution c_i to the service provider. The hardcore value assigned to each contributor is the cost for this contribution c_i minus its quality of contribution q_i, i.e.,

$$m_i = (1-\zeta)c_i - \zeta q_i, \quad (12)$$

where ζ is a weighting factor. Essentially, preference is given to contributors with a low cost and a high quality of contribution. The value of m_i is normalized. A contributor is selected if there is no other contributor in the neighbourhood with a smaller hardcore value.

4.2.2. Incentive for selected coverage-based contributors

As mentioned in Section 2.2.2, coverage-based consumption can be regarded as a free coarse-grained sensing information service. In order to retain contributors who are selected to contribute to coverage-based consumption, the service provider remunerates the selected coverage-based contributors in the following manner, using the revenue received from enquiry-based consumers:

$$R_i = \frac{b_i}{b_i + \Sigma_{-i}} \omega \sum_{j=1}^{N_s} r_j \mu_j, \tag{13}$$

where Σ_{-i} is the summation of contribution levels from all selected contributors except contributor i. Denote the intensity of the selected contributors as λ_m. The union of the sensing coverage of the selected contributors covers approximately 78% of the plane, which is sufficient for most environmental monitoring applications [22]. If a different sensing coverage is required, the selection scheme can follow the probabilistic Matern point process described in [20].

4.3. Combining the two incentives

A contributor can either be an enquiry-based contributor or a coverage-based contributor, or both. When a contributor is only an enquiry-based contributor or only a coverage-based contributor, it receives remuneration according to one of the aforementioned incentives, e.g., Eq. (11) for an enquiry-based contribution, or Eq. (13) for a coverage-based contribution.

When a contributor has a spatio-temporal relevant enquiry-based consumption and is also selected as a coverage-based contributor, it receives remunerations for both its enquiry-based contribution and coverage-based contribution. Thus, the remuneration for a contributor can be expressed as:

$$R_i = \begin{cases} (1-\upsilon-\omega) \sum\limits_{s_j^t \in \Phi_s(z_i^t)} \frac{b_i}{b_i + \Sigma_{-i,j}} r_j \mu_j & \text{if } \textit{enq-based ctr} \\ \frac{b_i}{b_i + \Sigma_{-i}} \omega \sum\limits_{j=1}^{N_s} r_j \mu_j & \text{if } \textit{cov-based ctr} \end{cases}$$

Both the incentives for enquiry-based and coverage-based contributors are implemented at the service provider, and the procedure is shown in Algorithm 1. The corresponding procedures for the contributors and consumers are shown in Algorithms 2 and 3.

5. Analysis and market equilibrium

As consumer demand varies over time and space, the contribution levels of the contributors should be adjusted accordingly. Conversely, the adjustment of contribution levels leads to the variation in the quality of consumption. In this section, we show that after the interaction between contributors and consumers through the service provider, a market equilibrium can be achieved where both contributors and consumers employ their optimal participation levels and the quality of consumption remains stable.

We adopt an interval-based approach where time is divided into review periods. In each review period, the contributors and consumers determine their optimal participation levels to maximize their utility functions.

Theorem 1. *The optimal contribution level which maximizes a contributor's utility is given by*

$$b_{opt} = \begin{cases} \frac{(1-\upsilon-\omega) n_s (n_z - 1) r \mu}{n_z^2 c} & \text{if } \textit{enq-based ctr} \\ \frac{\omega N_s (N_c - 1) r \mu}{N_c^2 c} & \text{if } \textit{cov-based ctr} \end{cases} \tag{14}$$

and $b_{opt} \geq 0$, where n_z is the average number of neighboring contributors around a consumer, n_s is the average number of neighboring consumers around a contributor, N_s is the number of consumers and N_c is the number of coverage-based contributors.

Algorithm 1 Algorithm for service provider.

```
During the review period, wait for an event:
if a contribution occurs then
    Evaluate and record the contribution with spatio-temporal
    tagged information;
end if
if enquiry-based consumption j occurs then
    Serve the consumer, provide service with quality of con-
    sumption Q_j and charge payment r_j;
    Remunerate the spatio-temporal relevant contributors ac-
    cording to Eq.(11);
end if
At the end of the review period:
for each contributor i do
    Assign hardcore value to contributor i, i.e.,
    m_i ← (1 − ζ)c_i − ζq_i;
end for
for each contributor i do
    Flag ← 1;
    for each contributor k in the spatio-temporal neighborhood
    of contributor i do
        if m_i > m_k then
            Flag ← 0;
        end if
    end for
    if Flag = 1 then
        Remunerate the coverage-based contributor according to
        Eq.(13).
    end if
end for
```

Algorithm 2 Algorithm for contributors.

```
for each contributor i do
    Receive remuneration R_i from the service provider that was
    calculated according to Eq.(11) or Eq.(13);
    Calculate the optimal b_i according to Eq.(14).
    Contribute sensor information at contribution level b_i in the
    next review period.
end for
```

Algorithm 3 Algorithm for consumers.

```
for each consumer j do
    Determine Q_j according to Eq.(6).
    Calculate the optimal μ_j according to Eq.(19).
    Consume the service at rate μ_j in the next review period.
end for
```

Proof. Contributor i should choose the optimal contribution level b_i to maximize his utility function (see Eq. (2)). In order to determine the optimal contribution level, we take the first order derivative of u_z in the case of an enquiry-based contribution as

$$\frac{\partial u_z}{\partial b_i} = \sum_{s_j^t \in \Phi_s(z_i^t)} \frac{(1-\upsilon-\omega)\sum_{-i,j}}{\left(\sum_{-i,j} + b_i\right)^2} r_j \mu_j - c_i. \tag{15}$$

The second order derivative of u_z is

$$\frac{\partial^2 u_z}{\partial {b_i}^2} = -\sum_{s_j^t \in \Phi_s(z_i^t)} \frac{2(1-\upsilon-\omega)\sum_{-i,j} r_j \mu_j}{\left(\sum_{-i,j} + b_i\right)^3}. \tag{16}$$

As can be seen from Eq. (16), u_z is a strictly concave function of b_i for $b_i \in [0, \infty)$. As the value of u_z in Eq. (2) is 0 for $b_i = 0$ (because $R_i = 0$), and tends to $-\infty$ when b_i goes to ∞, it has a unique maximizer b_i. Thus, the best response for Eq. (2) can be obtained when

$\partial u_z/\partial b_i = 0$. This can be solved by gradient descent or the Newton algorithm.

Take n_z to be the average number of neighboring contributors around a consumer and n_s to be the average number of neighboring consumers around a contributor. For an enquiry-based contributor, setting Eq. (15) to zero and assuming that contributors and consumers have homogeneous characteristics[6] lead to the optimal contribution level:

$$b_{opt} = \frac{(1-\upsilon-\omega)n_s(n_z-1)r\mu}{n_z^2 c}. \tag{17}$$

Similarly, for a selected coverage-based contributor, the optimal contribution level can be obtained by setting the first derivative of Eq. (2) to zero. Taking N_s to be the number of consumers and N_c to be the number of coverage-based contributors, the optimal contribution level of a coverage-based consumption is given by

$$b_{opt} = \frac{\omega N_s(N_c-1)r\mu}{N_c^2 c}. \tag{18}$$

Hence, we obtain Theorem 1. □

Theorem 2. *The optimal consumption rate for consumer j which maximizes its utility is*

$$\mu_{opt}(j) = \frac{\beta}{r_j}Q_j - 1 \tag{19}$$

under the condition that $\beta Q_j \geq r_j$, where Q_j is the quality of consumption for consumer j.

Proof. After each contributor decides on its contribution level and the quality of consumption for a consumer is known, consumer j chooses the optimal consumption rate μ_j to maximize its utility function in Eq. (3) by taking its first derivative and setting it to zero, i.e.,

$$\frac{\partial u_s(j)}{\partial \mu_j} = \frac{\beta Q_j}{1+\mu_j} - r_j = 0.$$

Thus, the best response can be obtained by solving the equation above and the optimal consumption rate for consumer j is given by

$$\mu_{opt}(j) = \frac{\beta}{r_j}Q_j - 1 \tag{20}$$

under the condition that $\beta Q_j \geq r_j$ to ensure that the consumption rate is non-negative. □

Theorem 2 gives the optimal consumption rate $\mu_{opt}(j)$ given the quality of consumption Q_j. This can be used to determine the optimal consumption rate for either enquiry-based consumption or coverage-based consumption. Since we treat coverage-based consumption as a free service in this paper, we shall consider only the case of enquiry-based consumption. Hence, the optimal enquiry-based consumption rate $\mu_j^e(j)$ given the quality of the enquiry-based consumption Q_j^e is

$$\mu_j^e(j) = \frac{\beta}{r_j}Q_j^e - 1. \tag{21}$$

Theorem 3. *There exists a market equilibrium and the resulting quality of consumption is*

$$Q_{me} = \frac{Gr}{G\beta - 1} \tag{22}$$

under the condition of $G\beta > 1$ and the initial quality of consumption $Q(1) = rG/(G\beta - 1)$ where

$$G = \frac{(1-\upsilon-\omega)n_s(n_z-1)\gamma}{n_z^2 c} \tag{23}$$

and

$$\gamma = \left\{ \frac{\lambda_s\left(1-e^{-\alpha T}\right)}{\alpha(1-\alpha)^2}\left[(\alpha-1)De^{(\alpha-1)D} - e^{(\alpha-1)D} + 1\right] - Te^{-\alpha T-(1-\alpha)D} \right\} \frac{1}{1-e^{-\alpha T-(1-\alpha)D}}.$$

Proof. In Eq. (6), Q_j^c has the same value for all $1 \leq j \leq N_c$, thus we ignore the index j. We have

$$Q_j = \xi Q_j^e + (1-\xi)Q^c \tag{24}$$

In Eq. (24), the average quality of enquiry-based consumption Q_j^e can be calculated as follows:

$$\begin{aligned} Q_j^e &= \mathbb{E}\left[Q^e\left(s_j^t\right)\right] = \mathbb{E}\left[\sum_{z_i^t \in \Phi_z\left(s_j^t\right)} w_{i,j}(t)\, q_i\right] \\ &= \frac{\mathbb{E}[q_i]}{1-e^{-\alpha T-(1-\alpha)D}}\left\{\mathbb{E}\left[\sum_{i=1}^{n_z} e^{-\alpha\Delta t_{i,j}-(1-\alpha)\Delta d_{i,j}}\right] - \mathbb{E}[n_z]e^{-\alpha T-(1-\alpha)D}\right\} \end{aligned} \tag{25}$$

In Eq. (25), assume that the temporal distribution and the spatial distribution of contributions are independent of each other. Hence, we have

$$\mathbb{E}\left[\sum_{i=1}^{n_z} e^{-\alpha\Delta t_{i,j}-(1-\alpha)\Delta d_{i,j}}\right] = \sum_{i=1}^{n_z}\mathbb{E}\left[e^{-\alpha\Delta t_{i,j}}\right]\mathbb{E}\left[e^{-(1-\alpha)\Delta d_{i,j}}\right] \tag{26}$$

In Eq. (26), assume that the contributors are spatially deployed according to a Poisson point process. From the property of a Poisson point process, we have

$$\begin{aligned} \mathbb{E}\left[e^{-(1-\alpha)\Delta d_{i,j}}\right] &= \int_0^D e^{-(1-\alpha)x}\cdot\lambda_s\cdot x\,dx \\ &= \frac{\lambda_s}{(1-\alpha)^2}\left[(\alpha-1)e^{(\alpha-1)D}D - e^{(\alpha-1)D} + 1\right] \end{aligned} \tag{27}$$

where λ_s is the spatial intensity of the contributors. From reference [11], we have

$$\mathbb{E}\left[e^{-\alpha\Delta t_{i,j}}\right] = \frac{1}{\alpha T}\left(1-e^{-\alpha T}\right). \tag{28}$$

Substituting Eqs. (27) and (28) into Eq. (25), we obtain

$$Q_j^e = \gamma\,\bar{\eta}\,\mathrm{E}[q_i] = \gamma\, b^e \tag{29}$$

where γ was defined above, $\bar{\eta}$ is the average contribution rate and b^e is the average contribution level of an enquiry-based contributor.

The quality of the coverage-based consumption is the union of the sensing coverage provided by coverage-based contributors. As the sensing coverage of each contributor does not overlap according to the properties of the Matern point process, Q^c can be calculated from Eq. (10) as

$$Q^c = \kappa\sum_{i=1}^{N_c} A\left(z_i^t\right)q_i = \kappa A\left(z_i^t\right)\lambda_m\mathbb{E}[q] = \kappa\lambda_m b^c \tag{30}$$

where λ_m is the intensity of Matern point process which can be calculated following [20] and b^c is the average contribution level of a coverage-based contributor.

[6] Hence, we can omit the i subscript in c_i and j subscript in r_j and μ_j and simplify the analysis.

Table 2
Main parameter settings in the simulation.

Parameter	Meaning	Default value
T	Temporal expiration range (hour)	1
D	Spatial expiration range (m)	10
N_z	Number of contributors	100
N_s	Number of consumers	10 or 20
α	Weighting of time vs space for spatio-temporal relevance	0.5
β	Scaling factor in Eq. (3)	18
ξ	Weighting of enquiry-based consumption	0.5
υ	Commission fraction of service provider	0.1

With the average quality of consumption, we can now calculate the market equilibrium. We divide the time axis into review periods with index m. In each review period, the optimal contribution level is determined using Eq. (14) given the remuneration. Similarly, in Eq. (19), the optimal consumption rate is calculated under the assumption that the quality of consumption is given. The total remuneration in the mth review period,

$$R(m) = N_s\mu r = N_s[\beta Q(m) - r] \tag{31}$$

Since we treat coverage-based consumption as a free service which does not affect the remuneration for contributors in this paper, we shall consider only the enquiry-based consumption when deriving the market equilibrium. Substituting $r\mu = R(m)/N_s$ into Eq. (14), we get

$$b^e(m+1) = \frac{(1-\upsilon-\omega)n_s(n_z-1)R(m)}{n_z^2 N_s c} \tag{32}$$

$$Q^e(m+1) = \gamma b^e(m+1). \tag{33}$$

When the quality of consumption tends to an equilibrium value, we have $Q^e(m) = Q^e(m-1) = Q_{me}$, which leads to the result in Eq. (22). □

6. Performance evaluation

6.1. Simulation settings

We performed extensive simulations to evaluate the effectiveness of the proposed STI scheme. In the simulations, multiple contributors and consumers are deployed according to a Poisson point processes with different intensities within an application area of 100 m × 100 m. We divide the time axis into review periods, where the review period is 1hour in the simulation. The contribution and consumption traffic arrive following a Poisson process at the determined contribution rate or consumption rate. The simulation parameters are shown in Table 2.

In the simulation, the quality of consumption is computed as the actual experienced quality of consumption shown in Eq. (6). Similarly, the remuneration received by a contributor is the actual remuneration calculated in Eq. (11) or Eq. (13). We run the simulation fifty times with different initial conditions and then calculate the average results. We study the performance of the STI scheme in two scenarios: (a) uniform static scenario: contributors and consumers are uniformly distributed and static. (b) non-uniform static case: contributors and consumers may congregate at certain areas instead of being uniformly distributed. The deployment of the non-uniform static scenario is obtained from traces of actual wireless users on a campus [23]. Moreover, we investigate the effect of the spatial distribution of the consumers with respect to that of contributors.

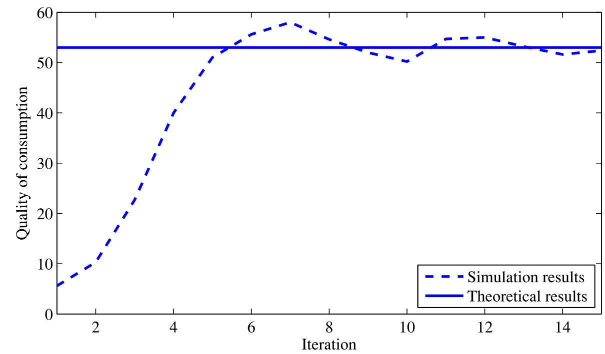

Fig. 5. Comparison of quality of enquiry-based consumption via analysis and simulation in the uniform static scenario.

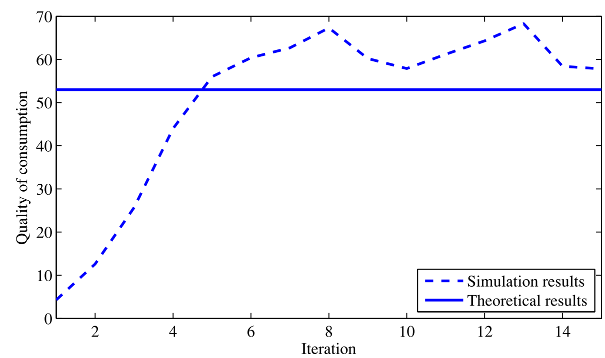

Fig. 6. Comparison of quality of enquiry-based consumption via analysis and simulation in the non-uniform static scenario.

6.2. Simulation results

6.2.1. Convergence of the quality of consumption

Fig. 5 shows the comparison between the theoretical results and simulation results under the uniform static scenario. As can be seen, after three or four iterations, the simulation results converge to the theoretical result, and then fluctuates slightly around the theoretical results. This means that in the uniform scenario, the simulation results fit well with the theoretical results.

Fig. 6 compares the theoretical and simulated quality of consumption in the non-uniform static scenario. It can be seen that the simulated average quality of consumption is higher than the theoretical results. This is because the theoretical results assume uniformly distributed contributors and consumers, while the proposed STI scheme can adjust the contribution levels according to the spatio-temporal demand of the consumers, thus leading to higher quality of consumption.

6.2.2. Payment to the contributors

Fig. 7 shows the comparison of the payment to the contributors using the STI scheme with that using the QCS scheme in [11] in a low contributor density scenario. As can be seen, the payment to the contributors using the STI scheme is lower than that using the QCS scheme. This is mainly because, in the STI scheme, remuneration is not made to contributors outside the spatio-temporal relevant region. As the number of consumers in the application area increases, the increase in the payment to the contributors using the proposed scheme tapers off as only a few of the new consumers fall in the spatio-temporal relevant regions of the contributors, and vice-versa.

6.2.3. Effects of spatial distribution of the consumers

Fig. 8 shows the quality of consumption when contributors are spatially distributed following the uniform distribution. Fig. 9

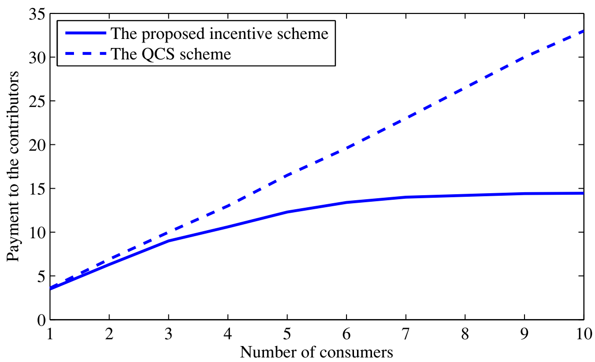

Fig. 7. Comparison of payment to contributors using the proposed STI scheme and the QCS scheme.

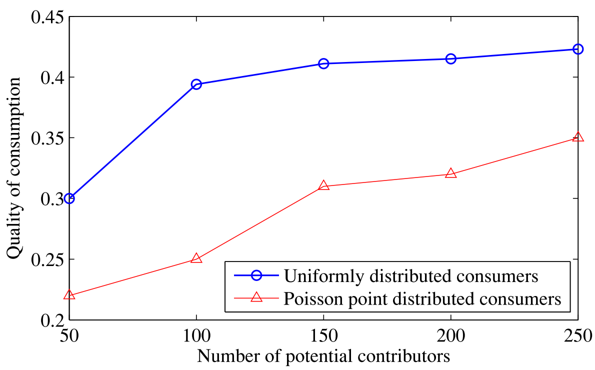

Fig. 8. Quality of consumption when contributors are under the uniform distribution.

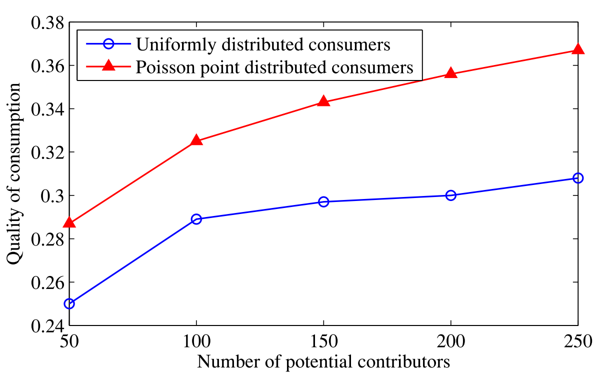

Fig. 9. Quality of consumption when contributors are under the Poisson point distribution.

shows the quality of consumption when contributors are spatially distributed following the Poisson point process. It can be seen that when the consumers and contributors follow similar spatial distributions, the quality of consumption is higher. This is due to the higher level of coupling arising from the closer proximity between consumers and contributors when they follow similar spatial distributions.

6.2.4. Spatial distribution of quality of consumption

Fig. 10 and 11 show the spatial distribution of quality of consumption in the application area with different numbers of consumers. The base plane $z = 0$ shows the spatial distribution of the contributors and consumers. The quality of consumption is calculated at each point in space as if a consumer is there. Contributors determine their optimal contribution level by Eq. (14). As can be seen, the quality of consumption at the areas where consumers congregate is higher than that at the areas with few consumers.

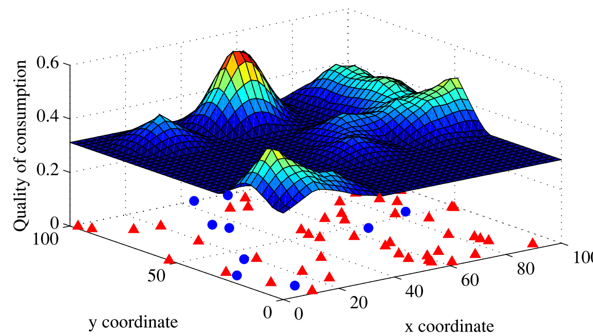

Fig. 10. Spatial distribution of quality of consumption with 10 consumers. (Legend: blue dots depict consumers, red triangles depict contributors.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

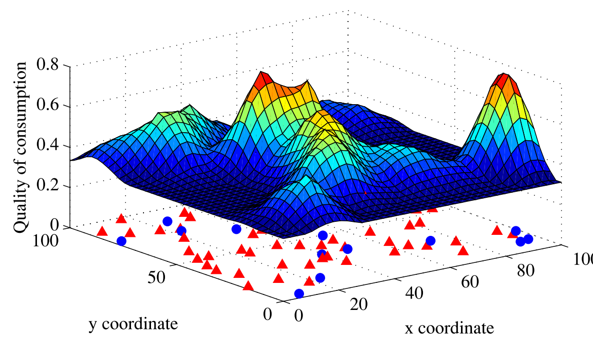

Fig. 11. Spatial distribution of quality of consumption with 20 consumers. (Legend: blue dots depict consumers, red triangles depict contributors.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

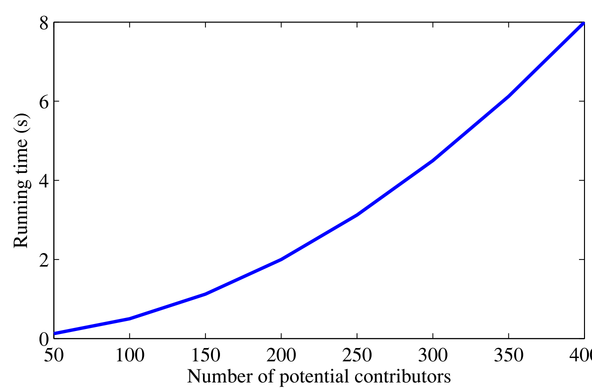

Fig. 12. Time complexity of the STI scheme.

This is because the STI scheme incentivizes the contribution levels according to the spatial distribution of the consumers. In Fig. 10, at the areas with no enquiry-based consumption, the contributors only maintain a minimum contribution level for coverage-based consumption. In Fig. 11, with the increased number of consumers, the quality of consumption is higher at more positions in the application area.

7. Discussion

Fig. 12 shows the running time of the algorithms in the STI scheme[7] versus the number of the potential contributors N_z. It

[7] The running time shown is for 15 review periods or iterations for convergence as shown in Figs. 5 and 6 executing on an Intel Core i5 PC running at 2.5 GHz.

can be seen that the consumed time increases quadratically with the number of contributors, as expected, since: (i) the selection of the enquiry-based contributors and the computation of the remuneration R_i takes $O\left(N_s N_z^2\right)$ operations, and (ii) the selection of the N_c coverage-based contributors also takes $O\left(N_z^2\right)$ operations. This should not pose a challenge since Algorithm 1 is implemented at the service provider.

Algorithms 2 and 3 can be executed in a distributed manner at each contributor and consumer, respectively. Each expression in the algorithms is computationally light with only several multiplications and summations. The only fairly complex quantity that needs to be evaluated is the quality of consumption Q_j in Algorithm 3. This quantity can be computed by the service provider and conveyed to consumer j since the service provider knows the set of spatio-temporally relevant contributors for a particular consumption, or it can also be approximated by the subjective experienced quality of consumption by the consumer.

Figs. 5 and 6 show that the STI scheme converges in about seven review periods or iterations. More generally, we expect the speed of convergence of the proposed algorithms to depend on the density of contributors and the variance of their sensor readings. Recent research results [24] indicate that the optimal sensor density to achieve the minimum mean-squared error metric in wireless sensor networks decreases as spatial correlation increases. Further study is required to see how these results can be extended to the participatory sensing case as it implies that not all spatio-temporally relevant contributors of a consumption need to be selected if their measurements are correlated. This can lead to faster convergence and lower computational complexity of the STI scheme.

The system architecture shown in Fig. 1 and the framework and algorithms proposed in this paper requires the existence of a service provider, which is an intermediary party which collects contributions from contributors, performs some information processing and provides the processed information to consumers. It is also responsible for calculating the remuneration to contributors. In the real world, this service provider is not an existing entity and has to be set up to facilitate the STI scheme presented in this paper. However, it is fairly straightforward and inexpensive to set up this service provider, i.e. a server with Internet connectivity would be sufficient if the volume of contributions and consumptions is not very high. If the geographical coverage region is large and there are many contributors and consumers, the service provider can be implemented on a public cloud, which is again not difficult or expensive to set up. There are many mobile applications which exist today that effectively leverage public clouds for content, storage and processing.

Sensing using the sensors on the smartphone and transmitting the sensed data to the service provider would consume some energy on users' smartphones. Since smartphone sensors and wireless radios are very energy-efficient these days, the energy consumption should be reasonable under normal operating circumstances. There is also no need to do any computationally intensive processing on the smartphone. As mentioned earlier in this section, Algorithms 2 and 3 which execute on smartphones for contributors and consumers, respectively, can be computationally light.

The parameter values in Table 2 cover application-dependent aspects such as the longest time and largest distance for a contribution to be considered spatio-temporally relevant to a consumer, the weightage between temporal and spatial components in the spatio-temporal relevance, the fraction of revenue charged by the service provider as commission etc. For example, a participatory sensing application for haze sensing is likely to have different parameter values from another participatory sensing application for road traffic conditions. The proposed algorithms will work for different parameter values and the theorems and results shown in this paper would still be valid.

8. Related work

Auction schemes have been employed for contributor selection in participatory sensing. Lee et al. [10] designed a reverse auction based dynamic price incentive scheme where contributors sell their sensing data to a service provider with their claimed bid prices, and the service provider pays for the contributors to minimize and stabilize the incentive cost while maintaining an adequate number of participants. Jaimes et al. [19] considered location information in the auction incentive mechanism with a greedy algorithm that selects a representative subset of the users according to their location given a fixed budget. Yang et al. [12] considered two system models: a platform-centric model where the platform provides a reward shared by participating users, and a user-centric model where users have more control over the payment they will receive. These works consider the interaction between contributors and the platform or service provider, but neglect the utility of the consumers.

Tham and Luo [11] formulated and analyzed a market-based framework for participatory sensing that considers the timeliness of the contributed data, and a resulting quality of contributed service (QCS) is derived. However, the important spatial aspect was not considered.

Spatial information of the contributors is important in incentive schemes in order to sustain a sufficient sensing coverage region in participatory sensing [25–27]. Moreover, some methods of information consumption in participatory sensing rely on spatio-temporal neighboring contributions rather than contributions over the entire sensing coverage region [18,19]. Hence, it is important to investigate the spatio-temporal relevance between contributors and consumers in participatory sensing so that contributions can be incentivized according to consumer demand, especially in scenarios with congregated consumers such as in metropolitan areas.

9. Conclusion

In this paper, we have proposed a spatio-temporal incentive scheme with consumer demand awareness for participatory sensing. Contributors are incentivized dynamically according to the consumer demand considering both enquiry-based consumption and coverage-based consumption. Only spatio-temporal relevant contributors for enquiry-based consumption and a subset of contributors which provide sufficient sensing coverage for coverage-based consumption are remunerated, which lead to a targeted and economical incentive scheme. A market equilibrium has been achieved where the optimal contribution level and optimal consumption rate are employed. The performance of the proposed incentive scheme has been investigated through extensive simulations which show improved quality of consumption and sensing coverage.

In future work, we will investigate the effect of user, i.e. consumer and contributor, mobility on the performance of the proposed incentive scheme and validate our theoretical results on an actual smartphone-based participatory sensing platform which we have developed.

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