Abstract—Users roaming cellular signal coverage with their mobile devices essentially form a mobile cyber-physical system (CPS). By modeling cyber human mentality and physical signal coverage, as well as their interplay, user mobility can be leveraged to improve users’ mobile experience with limited wireless bandwidth. Through a real-world case study, we observed that numerous “null zones” and “hot zones” exist in cellular signal coverage areas, where mobile devices cannot obtain sufficiently high data rates for delay-sensitive applications. Over one-third of the locations in a crowded area could have weak signal coverage and low bandwidth shares, resulting in poor mobile connectivity experience. This paper considers the practicality of a mobile CPS called Oasis, which guides users to leave those zones and move to nearby locations with better mobile experience. To realize the system, we model and maximize a user’s willingness to travel to another location, where the willingness involves the compound impact of the travel distance and the improved perceptual quality. We also develop a prototype system that creates a feedback control loop to allow self-adaptation to users’ needs.

To evaluate the efficacy, we conducted a series of experiments based on the real data collected in downtown Taipei. The results demonstrate that our mobile CPS can further reduce the average distance per unit of quality improvement achieved with OpenSignalMaps by about 80%, and motivate further research.

Index Terms—Mobile experience, user willingness, cellular signals, delay-sensitive applications, human-in-the-loop, cyber-physical systems

1 INTRODUCTION

Mobile cyber-physical systems (CPSs) exploit mobile sensing and computing devices tightly connected via communication networks to augment human interaction with the physical world. When a mobile user is using an application, his reaction and the application status are captured by the mobile device equipped with some sensing or measurement modules, and the captured measurements are conveyed to a cloud server that then analyzes the quality of the application in service provisioning. The analytical results, along with concurrent physical conditions, are used to adjust subsequent operations. A mobile CPS can have an internal control loop that exploits human feedback to make the service self-adaptable and more personalized. Mobile CPSs have recently enabled emerging applications to tackle societal problems, such as dynamic vehicle balancing [20], last-mile transit planning [30], and driving speed advisory [31].

Mobile device users roaming in a cellular signal coverage area provide an ideal infrastructure of a mobile CPS. In cellular systems, insufficient bandwidth is a persistent problem for delay-sensitive mobile applications [19], as new communication technologies often spark previously unforeseeable mobile applications, and vice versa. The problem is complex due to user mobility [28]. Modeling and understanding cyber-physical interactions between user perception and signal coverage could facilitate the empirical design of a mobile CPS which leverages user mobility to improve users’ mobile experience given limited wireless bandwidth. Specifically, when a mobile application cannot be executed smoothly due to a lack of bandwidth at a location, the mobile CPS allows for the visualization of surrounding signal strengths and helps the user find nearby locations with perceptually improved quality of the used application.

To this end, we conducted a case study in a crowded area covered by cellular signals in downtown Taipei, and observed that the ISP only deployed enough base stations to handle normal traffic levels because of cost considerations. However, the deployment leads to “null zones” with extremely weak signals and cannot satisfy the demand of “hot zones” where numerous users share the limited bandwidth simultaneously. Our statistical results show that nearly half the area is covered by such null and hot zones. As a result, there was a 60-70% chance that an HSDPA-enabled smartphone could not obtain a sufficient data rate for video streaming, and about a 20% chance that it could not browse websites smoothly. For an HSPA+-enabled tablet tested in the same experiments, the chances were 20-30% and 4-7% respectively.

Motivated by the above results, we propose a mobile CPS called Oasis, which guides users to move from those zones to nearby locations that have sufficient bandwidth. Oasis exploration could be realized as a value-added service offered by Internet service providers (ISPs) because they usually maintain signal coverage maps and monitor radio resource usage for network planning, e.g., capacity and coverage optimization [12]. They could further exploit the collected information to provide the service, and thereby improve users’ mobile experience while reducing their own deployment costs. However, offering the service raises several challenges in modeling cyber human mentality and physical signal coverage, as well as their interactions. The first is how to model a user’s satisfaction with an application at different locations. Another challenge is how to quantify

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and maximize a user’s willingness to travel to a location. This is particularly difficult because the willingness involves the compound impact of the travel distance and the improved perceptual quality, as well as depends on the application being used. Finally, it is also challenging to present the service in a way that is intuitive and requires minimum user intervention. Meanwhile, the service should be self-adaptive to fit each user’s needs because subscribers may have different preferences, e.g., shorter travel distances or better perceptual quality.

In this paper, we posit the practicality of the mobile CPS to provide the oasis exploration service. Our contributions are as follows. First, we formulate the underlying problem of the service that requires accounting for the role of humans in the loop. Specifically, we link a user’s satisfaction with an application’s perceptual quality in different locations, and quantify the user’s willingness to travel to different locations in exchange for better perceptual quality. Then, we solve the underlying problem, which involves finding an accessible location that maximizes the user’s willingness. Next, we describe the prototype mobile CPS that we built to realize the service. The system, which is comprised of an online server and an Android mobile app, creates a feedback control loop to allow self-adaptation. Further, we conducted a series of experiments based on the real data collected in downtown Taipei. The results demonstrate that the service can capture users’ travel intentions, and gradually converge toward users’ needs. We observed that a subscriber using an HTC smartphone or ASUS tablet can usually gain a significant improvement in perceptual quality as a trade-off for traveling a reasonable distance. The average distance per unit of quality improvement is only one-fifth that required by an approach motivated by OpenSignalMaps. Our experiments showed that the oasis exploration service is practicable. Finally, based on the experience learned from this study, we identify issues which require further investigation and discuss possible extensions for future research.

The remainder of this paper is organized as follows. Section 2 describes the case study we conducted in Taipei. In Section 3, we formulate and solve the underlying problem. Section 4 presents the implementation of the prototype system. The experiment results are reported in Section 5. Section 6 discusses the limitations of our work and future extensions. Finally, we review related work in Section 7 and draw our conclusions in Section 8.

2 WHY OASIS EXPLORATION?

In this section, we establish the motivation for oasis exploration through a real world case study, which shows that a stronger signal does not always imply a higher data rate and the data rates provided by ISPs are not always satisfactory. We consider some of the major causes and explain how oasis exploration can help solve the problem.

2.1 A Real-World Case Study

The data rate varies from location to location and often changes over time. A real-world case study needs the instant data rate at every location to analyze the variation in bandwidth. From the perspective of an ISP, it is not hard to perform instant data rate estimation, which will be discussed in more detail in Section 6.1. In this study, we collected data rates in a way similar to that Google collects street views. It is well known that the data rate achievable at a location depends highly on the signal strength (due to the adaptive modulation and power control in wireless systems [23]) and the users who share the bandwidth (due to the shared nature of radio networks [12]). Because the signal strength at a location is generally stable [23], analyzing the distribution of signal strengths provides a good sense of data rates achievable at different locations. Moreover, understanding how bandwidth is shared by users helps identify the variation in data rates among locations. Although the data was not collected in a real-time manner, the analytic results could still provide a general pattern of data rate distributions and are adequate to draw major causes of bandwidth insufficiency.

![Fig. 1. A case study in the Xinyi New Life Square](image)

We chose a crowded area of downtown Taipei called the Xinyi New Life Square for the study. As shown in Figure 1(a), the area measures 450×900 m² and contains a number of facilities, such as bus stations, office buildings, and department stores. Since the communication capabilities could have affected the study’s outcomes, we considered two Android devices, an HTC EVO 3D smartphone and an ASUS MeMO Pad 10 tablet, which have different hardware specifications. The smartphone features HSDPA connectivity with a theoretical data rate of 14.4 Mbps, while the tablet features HSPA+ supporting a downlink data rate of up to 21 Mbps. A mobile app developed by OpenSignalMaps was installed on each device to measure the signal strengths (dBm) and the corresponding downlink data rates (Kbps) at various locations in the area, as well as to locate the base stations that serve the area, as shown in Figure 1(b). It has been observed that poor signal strength is routinely experienced by mobile users, both spatially and temporally [7]. To capture the spatial variance, we made 10 independent measurements at each of 190 locations, spaced every 30 meters, within the area. In addition, to determine the temporal variance, we made the measurements during two periods on weekdays: daytime (from 10 a.m. to 5 p.m.) and evening (from 6 p.m. to 10 p.m.). As a result,
each device collected approximately 1900 samples for each period, i.e., 7600 samples in total. The compiled data sets are called Phone@daytime, Phone@evening, Tab@daytime, and Tab@evening, respectively.

2.2 Null Zones - Weak Signal Strengths

Fig. 2. The CDF of signal strengths

Because the signal strength has a direct impact on the downlink data rate [23], we first analyze the cumulative distribution function (CDF) of the collected signal strengths. Figures 2(a) and 2(b) show the CDFs of the signal strengths in Phone@daytime and Phone@evening respectively. The signal strengths are distributed widely and evenly over the range [-90,-50] dBm. Based on statistical analysis, the expected value of the signal strength is approximately -65 dBm, and the corresponding data rate in the signal-datarate model is 2.7 Mbps. In other words, there is a 50% chance that the data rate of the smartphone will be less than 2.7 Mbps. Figures 2(c) and 2(d) show that the signal strengths measured by the tablet have similar patterns to those of the smartphone. Although the tablet has a more powerful module, half of the signal strengths are still below the expected value of -60 dBm, with a corresponding data rate of up to 5.2 Mbps in the model. The results indicate that, in half the trials, both devices could only achieve approximately 25% of their theoretical data rates.

To analyze the causes of weak signal strengths, we plot the distribution of the signal strengths in Phone@daytime and the locations of the base stations in Figure 1(b). We observe that most base stations are erected along the area’s perimeter, with an inter-site distance of approximately 500 meters, so as to provide sufficiently large coverage in an economic manner, while additional base stations are set up at the most densely populated locations to improve the spectral efficiency. With such a deployment, the avenues

2.3 Hot Zones - Low Bandwidth Shares

Fig. 3. The CDF of bandwidth shares

The data rate measured at a location also depends on the users who share the bandwidth simultaneously. Thus, we estimate the traffic burden at a location by the bandwidth share, which is defined as the ratio of the data rate measured at the location to the data rate under the same signal strength in the signal-datarate model. Figures 3(a) and 3(b) show that the bandwidth shares of Phone@daytime and Phone@evening are spread over a wide range with about 50% below 1. For the tablet, about 30% and 50% of the bandwidth shares are below 1 during the day and the evening, as shown in Figures 3(c) and 3(d) respectively. Among the locations with bandwidth shares below 1, the maximum data rate measured by the smartphone is 4.1 Mbps during the day and 5.4 Mbps during the evening; while the comparable measurements for the tablet are 5.9 Mbps and 9.5 Mbps respectively. Surprisingly, during the evening, the maximum data rates achieved by the smartphone and the tablet in 50% of the area are only about 40% of their theoretical data rates. During the day, the devices could not achieve more than 28% of their theoretical data rates in 50% and 30% of the area respectively.

To conjecture the population distribution of mobile users in this area, we plot two respective bubble charts based
Fig. 4. Visualization of bandwidth shares

on the bandwidth shares with respect to Phone@daytime and Phone@evening. Figure 4(a) shows that the bandwidth shares at most locations near the bus station and the office buildings are below 1 (marked in purple bubbles) during the daytime, and some are even below 0.5 (red bubbles). However, they climb to above 1 (yellow bubbles) and even above 1.5 (blue and green bubbles) in the evening, as shown in Figure 4(b). A reasonable explanation for the phenomenon is that nine-to-fivers share the bandwidth during the daytime and leave the area in the evening. In contrast, the bandwidth shares near the department stores are relatively high during the daytime, but they drop to below 1 in the evening, as we observed that people usually crowd into this area for amusements after work. Interestingly, the bandwidth shares at the well-known landmark of Taiwan, Taipei 101, do not vary significantly for a whole day. It might because tourists come for short visits and leave soon for next spots at every moment. The bandwidth shares measured by the tablet also have similar distribution patterns. We observe that some hot zones with bandwidth shares below 0.5 formed during the day, but disappeared during the evening; and some are the opposite. The result is concurred with the well-known fact that the achievable data rate varies with the number of users who share the bandwidth. Thus, it is not economical to position base stations just to service peak-time traffic adequately [27].


In this section, we model cyber human satisfaction and willingness in a physical environment with dynamic cellular bandwidth, thereby establishing the theoretical models behind the mobile CPS. We formulate the oasis exploration problem (Section 3.1); explain how to estimate a user’s satisfaction with an application at different locations (Section 3.2); describe how to quantify a user’s willingness to travel to different locations (Section 3.3); and solve the problem of finding a location that maximizes the user’s willingness to travel (Section 3.4).

3.1 Problem Formulation

When a mobile user looks for a nearby location to obtain better perceptual quality for an application, he can choose one of the possible routes from the current location, as shown by the example in Figure 5. Accordingly, a better location will be found on each route. Finding such a location is considered an independent problem. More details about how to generate possible routes will be provided in Section 4.

Let $d$ denote the location that is $d$ meters from the original location on a particular route. Normally, a user is only willing to travel a certain (maximum) distance, denoted as $\bar{d}$; therefore, a location $d$ is deemed accessible if $d \in [0, \bar{d})$. Two factors affect a user’s willingness to travel. The first is the improved perceptual quality. To represent an application’s perceptual quality at different locations along a route, we employ a satisfaction function, denoted by $s(d)$ for any $d \in [0, \bar{d}]$. The second factor is the travel
distance. Intuitively, a user’s willingness is linked to the distance \(d\) as well as the perceptual quality \(s(0)\) and \(s(d)\) at the original location and the new location respectively. To quantify the user’s willingness to travel a distance \(d\) to improve the perceptual quality of \(s(d) - s(0)\), we define a willingness function, denoted by \(\omega(d, s(0), s(d))\). We explain how the two functions are derived in Sections 3.2 and 3.3 respectively.

A technical problem that arises in the above process is how to find an accessible location \(d \in [0, \overline{d}]\) on a route \(r\) such that the user’s willingness to travel to the location is maximized. We call an accessible location an oasis, denoted by \(o\), as shown by the green bullets in Figure 5. A mapping of a route to an oasis is called an oasis exploration. We formally define the problem as follows:

Instance: A route, \(r\), associated with a satisfaction function \(s(d)\) and a willingness function \(\omega(d, s(0), s(d))\), for \(d \in [0, \overline{d}]\).

Objective: Find an oasis \(o\) that is on the route \(r\) and maximizes the user’s willingness, i.e.,

\[
o = \arg \max_{d \in [0, \overline{d}]} \{\omega(d, s(0), s(d))\}.
\]

### 3.2 User Satisfaction Modeling

Next, we consider how to derive a satisfaction function, i.e., \(s(d)\), for \(d \in [0, \overline{d}]\), for a type of mobile application. Basically, mobile applications can be categorized into four types: streaming, interactive, conversational, and best-effort [12]. The Mean Opinion Score (MOS), which provides a numerical indication, is widely used to quantify user satisfaction with an application under various downlink data rates [16]. Many studies have tried to establish MOS functions for the above applications [2, 3, 8, 13, 18, 24]. With regard to the downlink data rate, any MOS function could be used for oasis exploration. In the following, we consider the first type of application, namely TCP-based video streaming, as an example. We describe its behavior and the rationale behind its MOS function.

TCP-based video streaming applications, such as IMDb, exploit TCP to deliver video content to end users, so that lost packets can be detected and retransmitted. However, if the downlink data rate is lower than the video bitrate, the video playback process will gradually empty the buffer and result in stalling events. Then, the user will experience intermittent video playback, which will impact his satisfaction. As indicated in [13], the number of stalling events and the length of an event are the decisive factors in user satisfaction. Given a video stream, the number of stalling events can be approximated by an equation that considers the video bitrate, the video length, and the downlink data rate. The length of a stalling event, which depends on the video playout buffer’s implementation, is usually a fixed integer. Based on the number of stalling events per video stream, an MOS function for video streaming was presented in [13] using crowdsourcing, a subjective quality evaluation method. Interested readers may refer to [13] for the function’s closed-form expression. Note that the MOS function borrowed from [13] was established for video streams with constant bitrate. For video streams with adaptive bitrate, like YouTube, the MOS function derived from [18] or [3] could be used instead.

Different types of application may have different MOS functions. For example, web browsing (like Chrome) and file synchronization (like Dropbox) are two popular applications that belong to the interactive and best-effort types of application respectively. User satisfaction is dominated by the page load time and the file download time [9], which can be calculated based on the downlink data rate plus the number and size of the data items to be downloaded [17]. Accordingly, their MOS functions with respect to the data rate were established in [9].

The satisfaction function for a type of application can be derived if its MOS function with respect to the downlink data rate has been established\(^3\). Given an MOS function, we map the downlink data rate at each location to an MOS value at the location, so each application type has its own satisfaction function with respect to the locations along a route. Because the MOS value varies irregularly along a route, we apply a polynomial regression method [29] to the MOS values and obtain a satisfaction function as follows

\[
s(d) = \sum_{i=0}^{q} a_i d^i, \quad d \in [0, \overline{d}],
\]

where \(a_i\) is the coefficient of the term with degree \(i\) and \(q\) is the highest degree of the polynomial.

### 3.3 User Willingness Modeling

Next, we explain how to derive a willingness function on a route, i.e., \(\omega(d, s(0), s(d))\), for \(d \in [0, \overline{d}]\), for an application type. The willingness to travel could be influenced by \(d\), \(s(0)\), and \(s(d)\); or by a combination of them. Let \(x\) be the vector of the seven combinations of the three influencing factors, i.e., \(x = (d, s(0), s(d), s(0)d, s(d)d, s(0)s(d), s(0)s(d)d)^T\), and let \(x(k), k = 1, 2, ..., 7\), denote the \(k\)-th element. Then, assigning the respective values to \(d\), \(s(0)\), and \(s(d)\) yields a corresponding setting of \(x\). Given a setting \(x_j\), let \(\pi(x_j)\) be the probability that the user is willing to travel. Now, we have to establish the relationship between \(x_j\) and \(\pi(x_j)\). Because the user’s response will be either Yes or No, the response to \(x_j\) is binary; thus, the relationship between \(x_j\) and \(\pi(x_j)\) is generally nonlinear. In statistics, logistic regression is widely used to predict the odds of being a case based on the values of the independent variables. Binary logistic regression (or called a logit model [1]) deals with situations when the response takes one of only two possible values representing Yes and No, or more generally the presence or absence of a variable of interest. Here, the variable of interest is user willingness, i.e., willing or unwilling to travel to an oasis in exchange for better perceptual equality.

Moreover, the nonlinear relationship is often monotonic, either increasing or decreasing continuously, where a fixed change in \(x_j\) often has less impact when \(\pi(x_j)\) is close to 0 or 1 than when \(\pi(x_j)\) is close to 0.5. Typically, such a relationship has a model formula [1] given by

\[
\pi(x_j) = \frac{e^{\alpha + \beta x_j}}{1 + e^{\alpha + \beta x_j}},
\]

3. For applications without MOS functions, our prototype system recommends the closest location with the strongest signal on each route instead.
where $\alpha$ and $\beta = (\beta_1, \beta_2, \ldots, \beta_T)^T$ are the coefficients of the formula. With some rearrangements, the log odds of $\pi(x_j)$ reveal the linear relationship, i.e.,

$$\log \frac{\pi(x_j)}{1 - \pi(x_j)} = \alpha + \beta^T x_j,$$

where the odds indicate a comparison between the probabilities to travel, i.e., $\pi(x_j)$, and not to travel, i.e., $1 - \pi(x_j)$. The above model is a logit model in which the responses to the same setting are treated as an independent binomial experiment. Undoubtedly, the larger the number (and the more diverse) the settings and the responses gathered, the more accurately the logit model will reflect the user’s willingness to travel. Suppose there are $N$ settings, i.e., $x_j$, for $j = 1, 2, \ldots, N$. We can simply use the maximum likelihood method [1] to determine a pair of $\hat{\alpha}$ and $\hat{\beta} = (\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_T)^T$ so that the response to each of the $N$ settings is the most probable. Then, the resultant logit model is derived by

$$\log \frac{\pi(x)}{1 - \pi(x)} = \hat{\alpha} + \hat{\beta}^T x,$$

where $\hat{\beta}_k$, $k = 1, 2, \ldots, T$, indicates the influence of the $k$-th element, $x(k)$, on the user’s willingness to travel.

There are seven elements in the vector $x$, but it is not necessary to include all of them in the logit model. Too few elements would not be sufficient to reflect the influence of the three factors on the log odds; in contrast, too many elements could disturb the estimation of the log odds. The objective of model selection is two-fold [1]: the selected model should 1) be complex enough to fit the data well, and 2) be relatively simple to interpret. We utilize Akaike Information Criterion to evaluate how well a model reflects the user’s willingness to travel. In addition, we use an iterative variable-selection method, called backward elimination, to eliminate unnecessary elements in the above logit model. Note that $\hat{\beta}_k$ is set at zero if it is the coefficient of an eliminated element $x(k)$. By substituting Equation (1) into Equation (2), the general form of the user willingness function on a route for an application type is given by

$$\omega(d, s(0), s(d)) = \hat{\alpha} + \hat{\beta}_2a_0 + (\hat{\beta}_1 + \hat{\beta}_3a_0)d + (\hat{\beta}_4 + \hat{\beta}_5a_0)\sum_{i=0}^{q} a_id^i + (\hat{\beta}_6 + \hat{\beta}_7a_0)\sum_{i=0}^{q} a_id^{i+1}.$$  

### 3.4 User Willingness Maximization

Finally, given a route associated with a user’s satisfaction and willingness functions, we explain how to search for an oasis that will maximize the user’s willingness to travel. As shown in Equation (3), after substitution and rearrangement, a willingness function is a function of $d$. In other words, we have to find a location $o \in [0, d]$ such that $\omega(o, s(0), s(o))$ is maximized. Because Equation (3) is a polynomial function, the location, $o$, can be determined by the first and second derivatives of the equation. By setting the first derivative, i.e., $\omega’(d, s(0), s(d))$, equal to zero and solving the derivation for $d$, Newton’s method can be used to obtain the roots of the first derivative. Let $\Delta$ be the set of roots. A root in $\Delta$ can be a maximum, minimum, or saddle point; however, it is only a maximum when the second derivative, i.e., $\omega''(d, s(0), s(d))$, is less than zero. Let $\Delta_c$ be the set of the roots in $\Delta$ such that the second derivative is less than zero. Note that, in addition to the roots in $\Delta_c$, the boundaries 0 and $7$ must also be considered in the maximization. Hence, an oasis that maximizes the user willingness function can be found by examining each location $d \in \{0, 7\} \cup \Delta_c$, i.e.,

$$o = \arg \max_{d \in \{0, 7\} \cup \Delta_c} \{\omega(d, s(0), s(d))\}.$$  

### 4 A MOBILE CPS FOR OASIS EXPLORATION

#### 4.1 Design and Implementation

Next, we describe a mobile CPS that runs the oasis exploration service, where the theoretical models discussed in Section 3 serve as the underlying techniques. Our oasis exploration system comprises an online server and an Android mobile app, as shown in Figure 6. The system is structured with a feedback loop control composed of three phases: the data collection phase, the oasis exploration phase, and the self-adaptation phase. In the data collection phase, all the data required to initiate the service is collected and stored in separate databases on the server. The oasis exploration phase is invoked when a mobile device containing the Oasis app sends a request to the server. On receipt of the request, the server searches for oases nearby and responds to the app. The app also provides a GUI to seek feedback from users to facilitate the adaptation of the service to their real needs in the self-adaptation phase. The design has several advantages. First, as the server performs most of the computations, mobile devices do not incur a significant overhead. Second, user intervention is minimized because nearly all the information needed is monitored automatically by the system. Third, the communication traffic is reduced because a request or response will only contain a small amount of information. Fourth, the service is adaptable to each user’s needs. This property is especially important because the initial satisfaction and willingness functions based on crowdsourcing studies may not accurately reflect a users’ needs. We discuss the three phases in detail in the following sub-sections.

#### 4.2 The Data Collection Phase

If the service is offered by an ISP, the data rate at a location can be estimated in a real-time fashion. More detail will be
discussed in Section 6.1. As mentioned in Section 2, for our case study, we collected downlink data rates in a small area of Taipei City in a way similar to that Google collects street views. Then, we split the collected data rates into four data sets (i.e., Phone@daytime, Phone@evening, Tab@daytime, and Tab@evening). To better manage the location-related data, we associated all the measured data with a geographic 2D coordinate reference system, called TWD97 that is used in Taiwan, and stored the data in a PostgreSQL database. In addition, we installed PostGIS, which adds support for geographic objects and allows location queries in PostgreSQL. For any location, we retrieved the corresponding data rates (or, if necessary, approximated the data rates using linear interpolation based on the rates collected nearby) and simply estimated its instant data rate at the average rate.

MOS functions and logit models are also relevant to users’ perceptions and are normally based on user studies. Our system implementation adopted the MOS functions for video streaming and web browsing described in [9, 13]. However, because users may have variant functions that may change slightly over time and space, they are deemed initial functions and will be updated based on each user’s feedback in the self-adaptation phase. Similarly, following the questionnaire design in [13], we devised our own questionnaire and conducted a simple user study to establish a preliminary logit model. We shot five videos that simulated different perceptual qualities of a type of application with MOS values ranging from 1 to 5; and we defined eight travel distances ranging from 50 to 400 meters with an interval of 50 meters. In each sample, two of the videos and a distance were selected at random. After watching the videos, the respondent was asked whether he would be prepared to travel the designated distance $d$ to gain an MOS increase of $s(d) - s(0)$, where $s(d) > s(0)$. We collected 640 samples from 80 respondents, 56 men and 24 women with ages ranged from 20 to 42 years, to establish a preliminary logit model. Even though some samples might be biased, the biases will be eliminated eventually during the self-adaptation phase. The MOS functions and logit model were stored in the PostgreSQL database for user satisfaction and willingness estimation, as described in Sections 3.2 and 3.3.

4.3 The Oasis Exploration Phase

If a mobile user is dissatisfied with an application’s perceptual quality, he can launch the Oasis app and check the application’s status, e.g., the current network-layer data rate acquireable via the TrafficStats class provided by Google, in the notification bar, as shown in Figure 7(a). The app asks the user to indicate the type of the application being used, as shown in Figure 7(b). Then, the map GUI implemented with the Google Maps API is presented. Google improves the accuracy of the GPS by using different kinds of information, like nearby Wi-Fi and cellular signals, as well as accelerometer and gyroscope data from the device. Consequently, when the accuracy of positioning in an urban area is sufficient for Google Maps, the oasis exploration service is usable there.

When the user touches the “Show Oases” button on the screen, the app sends a request (containing the user’s location and the application type and status) to the server running Linux. On receipt of the request, the server uses the query functions provided by PostGIS to retrieve the following information from the PostgreSQL database: the road segments within a radius of $d$ meters, the intersections of the segments, and the circle around the user’s location. On average, there are roughly 27 road segments within a radius of 500 meters. The server then invokes a PostGIS function that implements Dijkstra’s algorithm to find the shortest route to each of the intersections. For each route, the server derives the user’s satisfaction and willingness functions, and then searches for an oasis, as described in Section 3. Note that an oasis can be at an arbitrary distance within $[0, d]$, and is not necessarily a sampling location. To reduce the communication traffic, the discovered oases along with their shortest routes are stored in the JSON format and compressed in the MD5 format. Then, the compressed data, ranging from 1 Kbytes to 20 Kbytes (the average is 6 Kbytes), is sent back to the Oasis app in response to the user’s request. After receiving the response, the app displays the oasis information on the screen, as shown in Figure 7(c). The information about the surrounding signals can also be visualized, as shown in Figure 7(d), if the corresponding setting is enabled. The whole process takes about 8 seconds in general. In the prototype system, the possible routes
originated at the current location are processed sequentially. Since finding an oasis on each route can be considered an independent problem (as described in Section 3.1), the oasis exploration phase could be further speeded up with a parallel implementation.

4.4 The Self-Adaptation Phase

For self-adaptation, the Oasis app runs a daemon to periodically monitor the foreground application’s status, such as the downlink data rate. The daemon also gathers additional information if necessary. For example, it records a video’s bitrate and length when the video is streamed in the foreground. In addition, after the Oasis app is launched, it asks the user to rate the application’s perceptual quality, as shown in Figure 7(e). Then, it sends a request to the server for oasis exploration, as described in Section 4.3. When the daemon receives the server’s response, it starts to monitor the device’s position until the original application is switched back to the foreground to track the oasis picked by the user. After the application is terminated, the Oasis app asks the user to rate the perceptual quality again. The selected oasis, the two MOS values rated by the user respectively at the original location and the oasis, as well as the corresponding downlink data rates monitored by the daemon, are uploaded to the server. Note that the length of the monitoring interval has an impact on whether the measured data rate can reflect the actual data rate corresponding to the MOS value rated by the user. A long interval may not capture the up-to-date data rate, while a short interval may make the measured data rate sensitive to a bursty data rate. We adopt the average data rate over an interval of 5 seconds as an appropriate compromise. Finally, based on the feedback, the server adjusts the logit model and the MOS function to better fit the user’s needs after each service request.

To adjust the logit model, the server draws some reasonable inferences based on the selected oasis. Let the MOS value of the selected oasis be \( v \) and let its distance be \( d \). Moreover, let \( d^* \) denote the maximum distance of those oases whose MOS value is \( v \) and is selected by the user. If there are oases whose MOS values \( \geq v \) and distances \( d \), the user should also be willing to travel to them. In contrast, if there is any unselected oasis whose MOS value \( > v \) but whose distance \( d \), the user should be unwilling to travel to oases further away (if any) whose MOS values \( \leq v \). Moreover, for any unselected oases whose MOS values \( = v \), if their travel distances \( > d^* \), the user should be unwilling to travel to these oases; otherwise, the user should be willing to travel to the unselected oases whose distances \( \leq d^* \) if there is no better choice among discovered oases. Based on the inferences, the server generates new samples in a similar way to that described in Section 4.2; then, the logit model is adjusted based on all the samples in the database using the method described in Section 3.3. We sampled each MOS function taken from [9, 13] at 35 different data rates to generate initial samples and stored them in the database beforehand. Each pair of the uploaded MOS values and downlink data rates is added as a new sample. Because the relationship between MOS values and data rates is an exponential function [9, 13], the corresponding MOS function is adjusted using a nonlinear regression-based technique [22] based on the latest 35 samples (which are sufficient to derive an appropriate function in our study).

5 Performance Evaluation

5.1 Experiment Setup

To evaluate the efficacy, and better understand the properties of oasis exploration, we conducted extensive experiments in the Xinyi New Life Square. The Oasis app was installed on an HTC smartphone and an ASUS tablet, with the maximum distance \( \delta \) set at 500 meters; and the service was deployed on a Linux server based on the preliminary databases described in Section 4.2. In the experiments, we considered a TCP-based video streaming app, called IMDb, in accordance with the MOS function derived based on constant bitrate video streams in [13]. To assign appropriate parameters for the adopted MOS function, the Oasis app obtained the chosen trailer’s length and the video bitrate from the IMDb website automatically. We also measured a stalling event’s length (4 seconds) used in the implementation of the video playout buffer.

The oasis exploration service trades off the travel distance for improved perceptual quality. Thus, we evaluate its performance in terms of the improved MOS and the travel distance. Moreover, the failure rate is used as another metric to validate the service’s availability. The failure rate is the percentage of failed explorations over the total explorations conducted for all possible routes from a location, where an exploration is deemed a failure if the traveling distance per unit of MOS improvement is larger than the maximum distance \( \delta \) (i.e., the improved MOS value is only marginal or even negative).

To show the performance gain, we compared the proposed OASIS approach with an intuitive approach, denoted as MAXSIG, motivated by OpenSignalMaps. For each route, OASIS finds the location that maximizes a user’s willingness to travel, while MAXSIG recommends the closest location with the maximum signal strength. As observed in [23], downlink data rates are generally proportional to signal strengths. OpenSignalMaps, which visualizes the crowsource signal strengths in the form of color-coded maps, aids identifying accessible locations and motivates MAXSIG. However, MAXSIG does not consider applications’ perceptual quality and users’ travel intentions, which are reflected respectively by the MOS functions and logit models in OASIS. Comparison with MAXSIG allows us to understand the compound impact of the travel distance and the improved perceptual quality on users’ willingness to travel.

In Section 5.2, we consider some preliminary studies that helped us re-examine the design of the service and identify issues that require further enhancements. In Section 5.3, we address the identified issues and enhance the service; and in Section 5.4, we evaluate the performance of the service that has been adapted to meet users’ needs.

5.2 Preliminary Studies

For the preliminary studies, we chose an HD movie trailer, The Wolf of Wall Street, whose length is 153 seconds and video bitrate is 3022 Kbps. We watched the trailer and measured the average data rate at a randomly selected location.
Then, OASIS or MAXSIG searched for an accessible location on each of all possible routes that originated from the location. We walked to the oasis along each route and watched the trailer again in order to assess the travel distance and the perceptual quality. The experiment was performed on both devices during the day and the evening, and repeated at different locations with a variety of downlink data rates until a convergence of the performance trend was observed. We identified several issues that affected the efficacy of the oasis exploration service. The findings detailed below are based on 60 original locations, where the numbers of the selected locations for OASIS (/MAXSIG) were, respectively, 9 (/14), 6 (/7), 6 (/8), and 5 (/5) for Phone@daytime, Phone@evening, Tab@daytime, and Tab@evening.

First, we investigate the failure rates of MAXSIG and OASIS at each of the randomly selected locations with various downlink data rates. As shown in Figure 8, the failure rates of MAXSIG vary significantly with explorations at different locations. It is because MAXSIG recommends the closest location with the maximum signal strength along each route; however, a stronger signal does not always imply a higher data rate (and thus a larger MOS value) because the available bandwidth may be shared by multiple users. The average failure rates with respect to Phone@daytime, Phone@evening, Tab@daytime, and Tab@evening are 57.47%, 54.67%, 36.14% and 22.03%, respectively. In contrast, OASIS achieves the ideal failure rate of 0% at half of the 26 selected locations. One possible reason for the failures at the other half of the locations is that the data collected previously may not have accurately reflected the instant data rates because of users’ movements. The corresponding failure rates of OASIS are 35.14%, 18.18%, 9.09%, and 0%, respectively. Although OASIS is greatly superior to MAXSIG, the numerical results indicate the need of real-time radio resource estimation.

Next, we investigate the improved MOS. According to the borrowed MOS function [13], which maps a downlink data rate to an MOS value, the minimum and maximum MOS values of 1.62 and 4.97 for the trailer respectively occurs when the downlink data rate $\leq$ 2840 Kbps and $\geq$ 3220 Kbps. Figure 9 shows the improved MOS as far as those successful explorations are considered. Surprisingly, OASIS achieves the maximum or only marginal MOS improvements in different scenarios, but rarely yields modest improvements. We observed that traveling from a location

with a data rate of 600 Kbps to another with 2700 Kbps significantly improved the trailer’s perceptual quality; however, the MOS values under 600 Kbps and 2700 Kbps only made a marginal difference, and this exploration may be deemed a failure as a consequence. In other words, the preliminary MOS function’s effective range (i.e., from 2840 to 3220 Kbps [13]) is too narrow and cannot fit every user’s perception.

Finally, we investigate the traveling distances of those successful explorations. As shown in Figure 10, the traveling distances under MAXSIG vary significantly and irregularly within the maximum distance 7, i.e., 500 meters. The reason is that the strongest signal on a route can be at an arbitrary distance from the original location. Under MAXSIG, the traveling distance is approximately 300 meters on average. By contrast, the traveling distances under OASIS are much shorter. All the locations that
OASIS finds for the smartphone are within 300 meters and for the tablet are within 150 meters, which implies that the tablet can use a shorter traveling distance than what the smartphone needs to compensate for the same MOS improvement. This result indicates that the logit model is capable of reflecting users’ preferences for shorter distances but larger MOS improvements. However, after experiencing the travel distances, we found that the oases with distances ≥ 250 meters were beyond the acceptable distance. In other words, the preliminary logit model based on the indoor questionnaire cannot reflect users’ actual travel intentions.

5.3 Self-Adaptation of the MOS Function and Logit Model

To investigate whether the MOS function and logit model could adapt to an individual user’s needs based on his feedback, we considered five (kinds of) users with diverse preferences, as we observed based on the 80-responsive questionnaire study that users have different travel intentions but can be clustered into some representative cases. The users always selected the oasis whose MOS value was the largest within 50, 100, 150, 200, and 250 meters respectively. This setting allowed us to observe various results based on users with adequately different travel intentions. If no accessible oasis was found, they stayed at the original location. Moreover, after watching the trailer, they always rated the perceptual quality in accordance with a personalized MOS function, where the rating decreased exponentially from 5 to 1 when the data rate ≤ 3220 Kbps and ≥ 2500 Kbps. Each time a user watched the trailer, he did so at a location selected at random from the 190 sampling locations. The coefficient of determination, $R^2$, was used to assess how well an adjusted function fits the personalized function, with 1 representing a perfect fit. Meanwhile, the probability $p$ of an explored oasis located within a user’s preferred distance was used to assess the adjusted logit model, with 1 representing a perfect fit. The preliminary MOS function and model converge, as well as their stability, against different users. We then study how the preliminary function and model converge, as well as their stability, against different users.

Figure 11(a) shows how the preliminary MOS function converges toward the personalized MOS function according to the feedback from the user willing to travel within 150 meters. The convergence is not affected by the user’s travel preference; instead it is achieved when (1) samples with all possible MOS values are collected; and (2) the influence of the uploaded samples on the MOS function is sufficient to overwhelm that of the initial samples. As can be seen, the MOS function remains close to the preliminary function (with $R^2 = 0.56$ only) after 6 sets of feedback (each set contains two respective samples at the original and explored locations). The reason is that the data rates at numerous locations are below 2500 Kbps and the user always selects an oasis whose MOS value is the maximum within 150 meters. Consequently, the uploaded samples are mostly with MOS values of either 1 or 5. After 12 sets, some samples with medium MOS values are uploaded, and the function becomes close to the personalized function (with $R^2 = 0.80$). When the uploaded samples dominate the latest 35 samples, the MOS function eventually converges on the personalized function (with $R^2 = 0.94$) after 18 sets of feedback and adapts to the user’s needs.

Figure 11(b) shows how the preliminary logit model responds to the user’s actual traveling intention. The convergence is achieved when the uploaded samples are sufficient to reveal not only (1) the user’s willingness to travel within the tolerable distance, but also (2) the user’s unwillingness to travel beyond the tolerable distance even if there exist oases with higher MOS values. Thus, the logit model converges more quickly if the user is willing to travel a longer distance. Initially, the oases explored based on the preliminary model are distributed within 300 meters (with $p = 51\%$ of oases being within 150 meters). It indicates that the preliminary logit model, which was established based on the 80-responsive questionnaire study, cannot reflect the individual user’s actual travel intention. However, the traveling intention of the user willing to travel within 150 meters is gradually revealed after 6 sets of feedback, so some closer locations are explored as oases (with $p = 60\%$). Among 12 sets, some have indicated the user’s unwillingness to travel beyond 150 meters; thus, more locations within 150 meters are explored as oases instead (with $p = 79\%$). After 18 sets of feedback, the logit model only changes slightly. However, after the user returns 30 sets of feedback with similar travel intentions, the logit model changes dramatically and eventually adapts to the user’s needs, because all recommended oases are located within 150 meters (i.e., $p = 100\%$).

Table 1 shows how the preliminary function and model converge in response to the travel preferences of the five users. The $R^2$ values improve significantly after 6 sets of feedback, but they increase slightly after 12 sets. After 18

5. In statistics, the coefficient of determination represents how well a regression line fits the data. Its value (in the range 0 to 1) indicates the percentage of variation that can be explained by the regression line [29].
sets of feedback, the uploaded samples dominate the latest 35 samples, and the $R^2$ values approaches to 1. All the $R^2$ values for users with different travel preferences become 1 after 24 sets, indicating that the adjusted functions already fit the personalized MOS function, although the value of $R^2$ may converge at different rates for different users and slightly fluctuate during the convergence. The results show that travel preference does not have a significant impact on the convergence of the MOS function. Instead, the convergence occurs when the influence of the uploaded samples is sufficient to dominate the initial samples.

In contrast, the logit model converges more quickly if the user is willing to travel longer distances. We observed that, initially, the oases discovered based on the preliminary model are distributed within 300 meters. It appears that 6 sets of feedback are not sufficient to capture the travel intentions of the users who are only willing to travel within 150 meters because many oases are beyond the users’ preferred distances. However, 6 sets are sufficient to capture the travel intentions of the users who are prepared to travel 200 and 250 meters respectively. After 18 sets of feedback, more locations within the users’ preferred distances are identified as oases, because the unwillingness of the users to travel beyond 150 meters is captured after 18 sets of feedback. Then, after 24 sets of feedback, the adjusted models fit the corresponding users’ needs perfectly. Importantly, the MOS function and logit model that adjust to each user remain stable after 30 sets of feedback.

5.4 Experiment Results

Next, we evaluate the performance of the service that uses the MOS function and logit model adapted to each user’s needs in Section 5.3. Moreover, to simulate real-time data rate estimation (as if the service is offered by an ISP), it is assumed that the data collected previously is up-to-date at the time the users request the service. Although the experiment represents an ideal scenario, the results allow us to understand the characteristics of oasis exploration and draw some useful insights. The experiment setup is the same as that in Section 5.2, except that all 190 sampling locations are considered as original locations. First, we compare the performance of OASIS with that of MAXSIG, and then provide numerical results derived under various scenarios. It is expected that the MOS value of the location found by OASIS will not be smaller than that at the original location. Interestingly, MAXSIG may recommend a location that reduces the MOS value, which is deemed a failed exploration. The following results are based on the successful explorations.

Fig. 12. Improved MOS under a tolerable distance of 150 meters

Figure 12 shows the improved MOS under OASIS and MAXSIG when the user is unwilling to travel beyond 150 meters. In most cases, OASIS achieves the largest MOS improvement because it tries to find a location whose data rate $> 3220$ Kbps if possible; otherwise, it tends to search for a nearby location with a high data rate. With the MOS function adjusted, OASIS can achieve modest MOS improvements (between 2 and 4) sometimes. The exceptions with MOS gains below 1 are mainly because the original MOS values are already large enough or the user is unwilling to travel longer distances. Moreover, there are more exceptions in Figures 12(a) and 12(b) than in Figures 12(c) and 12(d) because it is quite difficult to find a location whose data rate $> 2500$ Kbps within 150 meters for the smartphone. Figures 12(c) and 12(d) only have few points because the tablet has already achieved a data rate $> 3220$ Kbps (which implies the maximum MOS value) at many original locations. Although MAXSIG recommends accessible locations regardless of the travel distances, in most cases, it achieves modest MOS improvements (instead of the largest MOS improvement). This is particularly obvious when other users share the limited data rates simultaneously at the recommended locations, as shown by the results in Figures 12(a) and 12(b).

Figure 13 shows the travel distances under OASIS and MAXSIG when the user is unwilling to travel beyond 150 meters. Nearly all the locations found by OASIS are within 150 meters, which indicates that OASIS is capable of determining the user’s travel intention. More interestingly, the average travel distance decreases with the downlink data rate at the original location. In other words, OASIS can capture the user’s unwillingness to travel far when the perceptual quality at the original location is relatively good. The average travel distance is approximately 83 meters when the data rate at the original location is low, but it is less than 12.5 meters when the data rate is high. According to
the results in Figures 12 and 13, a user who relies on OASIS needs to travel 22.5 meters to gain one unit of MOS improvement. In contrast, the travel distances under MAXSIG vary significantly and irregularly within 500 meters, with the average distance being approximately 325 meters. The results show that a user who relies on MAXSIG has to travel 110 meters to gain one unit of MOS improvement, which is 5 times that required by OASIS.

Table 2 shows the three quartiles, \( Q_1 \), \( Q_2 \), and \( Q_3 \), of the improved MOS, as well as the travel distance, under various scenarios. In general, the longer the tolerable travel distance, the greater the chance of gaining a larger MOS improvement. As indicated by \( Q_2 \), users willing to travel more than 150 meters have an even chance to trade off a travel distance of 35 to 115 meters for an MOS improvement of at least 3.93. Fortunately, for users who are unwilling to travel more than 50 meters, the MOS value can still be improved by at least 3.98 in one out of four trials, as indicated by \( Q_3 \). Moreover, users who are willing to travel 250 meters have 25%, 50%, and 75% chances of traveling no more than 75, 115, and 190 meters, respectively. For users prepared to travel 200 meters or more, similar oases are recommended because there are often locations that maximize the MOS improvement within 200 meters in the real environment. Note that users who are willing to travel longer distances will have more oasis choices. For example, 36 to 87 oases are found for users prepared to travel within 50 meters, while 67 to 558 oases are found for users prepared to travel within 250 meters. Moreover, the tablet generally explores oases with shorter travel distances than the smartphone does. For instance, as indicated by \( Q_2 \), the traveling distance for users who carry the tablet ranges from 10 to 55 meters, while the distance for users who carry the smartphone ranges from 15 to 115 meters. It indicates that the communication capability may affect a user’s decision. Regardless of the mobile devices used by the users, the results show that OASIS can capture their preferences for larger MOS improvements or shorter travel distances.

6. In descriptive statistics, the quartiles of a ranked data set are the three points that divide the set into four equal groups [4].

### 6. DISCUSSIONS

In this initial study, our major objective is to analyze the practicality of applying the proposed concept in real-world environments, rather than develop a fully functional oasis exploration system. Thus, we focus on addressing the most critical challenges, especially the modeling of users' willingness to travel and the adaption to their individual needs. Through extensive experiments based on a prototype system and real data, we have demonstrated the potentiality and benefits of the proposed mobile CPS. However, there remain several issues that require further investigation. In this section, we discuss some potential issues that may arise when the oasis exploration service is to be deployed by an ISP.

#### 6.1 Instant Data Rate Estimation

Oasis exploration relies on instant data rate estimation. Certainly, the more accurate the estimated data rate at each location, the more effective the service. Although an ISP can acquire the data rate at a location if any mobile users are accessing the Internet at the location [25], it is impractical to expect that a mobile user will be accessing the Internet, at any location, at any time, when the ISP would like to acquire the instant data rate there. However, it has been observed that the data rate achievable at a location depends highly on the signal strength and the users who share the bandwidth [12, 23]. An efficient and effective way is to estimate the data rate based on the signal strength at the location and the radio resource usage allocated by the base station that serves the location. The reason is as...
follows. Many cellular networks continuously collect signal strengths periodically reported by mobile devices. Because the signal strength at a location is generally stable [23], it can be collected whenever any mobile user accesses the Internet there (and/or approximated by an appropriate propagation model based on the collected strengths nearby). Moreover, an ISP usually monitors radio resource usage for network planning [12]. Therefore, the ISP could derive the theoretical data rate at a location based on the applied modulation scheme (which depends on the signal strength), and then estimate the instant data rate according to the real-time radio resource usage allocated by the corresponding base station. When the service is operated by an ISP, the data rate at any location could be estimated and updated in a more real-time fashion.

6.2 Reliability and Flexibility Enhancement

In Section 3, an accessible oasis, in the form of a specific point, determined by user willingness maximization is theoretically optimal with respect to the given data rates along a route. However, the instant data rates estimated by an ISP are not expected to be very accurate, because signal strength may fluctuate over time due to environmental factors and mobile traffic can change while the user walks toward the oasis. In other words, the determined oasis may, to some extent, fail to optimize the user’s willingness. This raises a critical question: how reliable is an oasis over time? In addition, exploring a particular location as an oasis sacrifices the flexibility for minimum user intervention. To enhance the flexibility and reliability, the current system shall be extended to explore a segment with a dynamic length, instead of a point, along each route. Basically, a probability model is required to present the variation in the data rate at each location so that the occurrence of a possible data rate is associated with a probability. The probability model can then be used to capture the variance in user satisfaction at the location. Accordingly, each oasis recommended will be associated with a successful probability, which is defined as the probability that the oasis succeeds in maximizing the user’s willingness. Importantly, when the user expects a high successful probability, a segment that contains an oasis with the designated successful probability will be recommended, instead of recommending a specific location. For example, if the user designates a successful probability of 100%, the range of the recommended segment could be as large as the maximum distance \( d \). In such a form, the user would be more comfortable and confident with the oasis exploration service.

6.3 Scalability and Congestion Avoidance

When the service is offered by an ISP, it is expected that the number of mobile users will increase tremendously. In our prototype system, the self-adaptation phase is performed on the oasis exploration server. To further improve the service’s scalability, this phase can be moved from the server to individual users’ devices. The rationale, which makes this movement possible, is that the MOS function and logit model are updated based on each individual user’s feedback, regardless of the feedback from others. Thus, each user is allowed to maintain a personalized MOS function and logit model on his own device. In addition, as observed in Section 5.3, the function and model gradually converge and remain stable after a few dozens of feedback. To avoid continually asking users for feedback, every user can decide whether to perform the self-adaptation phase, depending on whether the service already fits his needs. Whenever the function and model are updated, their coefficients must be uploaded to the server for use in the oasis exploration phase; however, there is no need to upload the user’s feedback to the server anymore.

Another issue may arise when users rush for specific oases. This, in turn, may introduce strong correlations in the movement patterns and give rise to the risk of bad user perception due to oasis overload. To avoid congestion, an approach should be employed for traffic control [14]. The rationale behind traffic control is as follows. After the Oasis app displays the information of the oases recommended by the ISP on a user’s screen, the app asks the user to indicate the oasis to be chosen, so that the ISP can estimate hot spots based on user mobility and increase the radio resource usage (allocated by the base station that serves the location) in advance before the user walks toward the chosen oasis. Consequently, those hot spots will be excluded automatically because the oasis exploration service tends to search for a nearby location with a high data rate.

7 Related Work

Mobile CPSs have recently enabled various emerging applications to tackle societal problems. In particular, Hull et al. [15] developed CarTel, a distributed sensing and computing infrastructure that uses various telematics devices to collect data about cars and road traffic in Boston and other metropolitan areas. Together with historical data, CarTel can be used for automotive diagnostics, road surface monitoring and hazard detection, as well as for traffic-aware route planning. Miao et al. [20] proposed a ride-sharing service based on a data-driven vehicle balancing model to coordinate taxis to fairly serve customers while reducing the total unoccupied driving distance. Evaluations based on four years of taxi data in New York City showed that the service significantly reduced the average total unoccupied distance. Zhang et al. [30] presented a transit service called Feeder, which employs existing cellular and transportation infrastructures to infer (transparently to passengers) last-mile transit demands and real-time traffic speeds so as to determine optimal routes for Feeder vehicles. Evaluated with large-scale cellphone and taxicab data collected in Shenzhen, Feeder was found to effectively reduce both last-mile distances and travel times.

Smartphones make ideal mobile CPSs. Mohan et al. [21] developed Nericell, a system that orchestrates smartphones carried around by users while driving, performing rich sensing and reporting data back to a server for aggregation to detect bumps and potholes, braking, and honking, thereby inferring road and traffic conditions. Thiagarajan et al. [26] presented VTrack, a system that uses smartphones as traffic probes, accurately estimating each user’s trajectory and travel time along a route to identify delay-prone segments and guide users to find better routes to particular destinations. Zhao et al. [31] implemented a smartphone-based intelligent speed adaptation system called GreenDrive, which uses crowdsourced vehicle movements to predict real-time traffic signal schedules and thus enable a speed advisory
service that reduces unnecessary accelerations and stops to reduce fuel consumption while meeting travel time requirements. The above mobile CPSs do not require modeling human mentality, such as user willingness, and little attention has been paid to human feedback that would allow for self-adaptation to users’ needs.

To mitigate the bandwidth shortage problem in cellular networks, it was recently advocated that ISPs should move towards time-dependent pricing by providing incentive prices to users for transferring their data traffic from peak to off-peak periods, thereby better managing the growing demand for bandwidth [10, 11]. The rationale behind the notion is that many mobile applications do not require real-time data transfer and can be deferred to less-congested periods. Thus, an ISP can flatten the temporal distribution of demand for bandwidth by offering reduced prices to motivate users to shift their data traffic in the timeline. Ha et al. [11] presented an architecture and implementation of a functional prototype, called TUBE, to realize time-dependent pricing for mobile data and conduct an experimental study. The trial results showed that TUBE benefits both ISPs and end users, allowing users to save money while ISPs flatten the temporal demand for bandwidth. Gabale et al. [10] applied the same concept to video content delivery. An asynchronous delivery system, called Async, was developed to demonstrate that leveraging the delivery times and prices can significantly improve overall user satisfaction with video playback. The results indicate that users are willing to shift their traffic if proper incentives are provided. The “time-shifting” solution can alleviate the bandwidth pressure in hot zones, but not in null zones. Motivated by the above results, we propose a “space-shifting” solution whereby users move from those zones to nearby accessible locations and realize the notion by a mobile CPS called Oasis. Time-dependent pricing and oasis exploration are orthogonal to each other, thereby alleviating the bandwidth shortage problem in the time and space domains respectively.

8 Concluding Remarks

We have presented a mobile CPS, called Oasis, to explore accessible locations for delay-sensitive mobile application. Oasis models an underlying optimization problem to maximize a user’s willingness to travel to a nearby location in exchange for better perceptual quality of the used application. The application’s perceptual quality and the user’s travel intention are characterized respectively by a self-adaptive MOS function and logit model. To validate the CPS system’s practicality, we designed a prototype implementation, which comprises an online server and a mobile app, to turn theoretical models into a practical oasis exploration service. Through extensive experiments based on real data collected in downtown Taipei with commercial mobile devices, we demonstrate that the service can often locate oases within users’ tolerable travel distances to significantly improve an application’s perceptual quality. Of course, the farther the user is willing to travel, the greater will be the improvement in the perceptual quality. The experiment results also provide valuable insights that will motivate further research.

In the future, we will address the reliability and congestion issues to further improve the OASIS system’s practicality. We will also enhance our mobile app so that we can crowdsource signal data more widely and frequently from mobile users, like OpenSignalMaps. Commercializing the service obviously involves addressing more challenges. We hope our initial efforts will stimulate further research.

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