Selecting Test location Data for Regression Testing of Mobile Location-Based Services

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Abstract

Location-based mobile information services provide nearby interesting information for mobile users. These services use user’s locations for their computations, making these services tend to treat locations in close proximity homogenously. The availability and validity of location-based mobile information services are often effected by mobile user location contexts, which make testing of location-based mobile information services become one urgent and challenging issue. In this paper, some test metrics have been proposed to select test data for regression testing of location-based mobile information service. Moreover, a case study is reported to describe our test approaches in details.

Keywords: Mobile testing; Location-based Services; Regression Testing.

I. INTRODUCTION

Location-based mobile apps provide many interesting and convenient location-based services (LBS) and functions, and bring many surprising and exciting user experiences [1]. For example, mobile app “Tripadvisor (tripadvisor.com)” helps to find nearby hotels and restaurants; mobile app “Momo (immomo.com)” helps to find nearby friends; and mobile game “Life is Crime (redrobot.com)” makes mobile players to fight with other players in the same location contexts.

Mobile location-based services have been identified as one of the most important features of mobile app services [2], and have become one hot research topic in mobile computing domains. In the recent years, there have been a number of published research papers addressing LBS. However, most papers primarily focus on infrastructure [3,4], positioning techniques [5], location privacy preserving [6,7], and other areas.

However, there are a few publications discussing mobile LBS testing until now. There is a lack of systematic and effective test approaches for test engineers to address mobile LBS testing. For mobile LBS testing, test engineers are often confused by selecting appropriate test location points in vast using zones.

This paper mainly do some research about test methods for selection test location data for regression testing of mobile LBS testing. The contributions of the paper include: a) A set of metrics are proposed to select test location data for regression testing of mobile location-based service; b) the case study are reported to analyze the cost-effectiveness of proposed regression testing techniques.

II. UNDERSTANDING MOBILE LBS TESTING

A. What is Mobile LBS Testing

Location-based services are information, entertainment, services that are conveniently accessible by mobile users through GPS-enabled portable devices and mobile networks (e.g., 2G/3G/4G cellular telephones and Wi-Fi networks). Some organizations and scholars have defined LBS, and the classic definition is presented below.

**Definition 1:** LBSs are information services accessible with mobile devices through the mobile network and utilizing the ability to make use of the location of the mobile device [15].

Based on our recent literature survey, there is a lack of published papers on LBS testing for mobile apps, and also no precise definitions of mobile LBS testing. Here we define it as below.

**Definition 2:** Mobile LBS testing refers to testing activities for native and Web apps on mobile devices to ensure quality in location-based functions, behaviors, information, and quality of service.

B. The Classifications of Mobile LBS

In recent years, mobile LBS have become more and more popular, and many mobile LBS apps are developed in various domains, such as navigation, information, emergency, advertising, tracking, games, management, and leisure. According to behavior characteristics of LBS, mobile LBS are divided into three types: basic location services, location context information services, and location context interactive services. Those services have different characters and features, and are compared in Table I.

**Basic location services** - The mobile apps provide basic digital maps, location, and navigation services to help mobile users find correct ways to their destination. Some early map and navigation apps provide basic location services for mobile users.

**Location context information services** - The mobile users search nearby location objects and then access or update information of location objects. Those location objects have fixed positions, and provide static or dynamic
information. Mobile users access information with push or pull ways. Most of information services are not real time services. The location context information services are widely used in many domains, for example, business, advertising, management, and leisure.

**Location context interactive services** - The multiple mobile objects interact with each other in same location contexts. Those mobile objects may be mobile users, smart cars, sensors, or other objects with positions. Location context interactive services provide different behaviors or functions according to locations or location relations between objects. Most of location context interactive services are real-time services, and are applied in some new domains, such as social networks, games and intelligent automobiles.

Today, there are hundreds of mobile apps with location-based information services, such as, Yelp, Booking, etc. So this paper focuses on regress testing of location-based mobile information services.

C. Why is Mobile LBS Testing Important?

Mobile LBS have been identified as killer services of mobile apps, which provide many conveniences and interests for mobile users. However, few published papers address the importance of mobile LBS testing. Here, its primary reasons and importance are listed as follows.

**Reason #1: Multiple techniques for LBS** - Mobile LBS normally use many different techniques, such as mobile computing, geographic information systems, GPS, cloud computing, Internet, etc. Those techniques make mobile LBS testing more complex.

**Reason #2: Location impact for LBS** - Location is the most critical factor for mobile LBS, which affects information, behaviors, functions, performance, dependability, privacy, etc.

**Reason #3: Higher costs of LBS testing** - Due to numerous locations, different kinds of location objects with changing information, and moving objects with unpredictable paths, the test engineers have to spend a lot of time and effort on mobile LBS testing.

III. TEST MODEL FOR MOBILE LBS

This section presents our proposed metrics for regression testing of mobile LBS.

A. Basic concepts and definitions

First, some basic concepts are defined. These concepts are important to design test cases for mobile LBS.

**Definition 3**: A location \( l_i = (\text{long}_i, \text{lat}_i) \) is a pair of real numbers representing the longitude \( \text{long}_i \) and the latitude \( \text{lat}_i \) of the location on the Earth surface.

**Definition 4**: The Distance \( \text{Dist}(l_i, l_j) \) denotes the shortest distance between two locations \( l_i \) and \( l_j \) on the Earth surface.

**Definition 5**: A set of test locations \( TL = \{P_1, P_2, \ldots, P_i, \ldots, P_n\} \) is a sequence of locations. which \( P_i \) is a location point.

B. Test metrics

This section presents our proposed metrics for test data selection.

- **Test location variance**

  Test location variance \( \text{var } (TL) \) measures the variance of a location sequence \( TL = \{P_1, P_2, \ldots, P_i, \ldots, P_n\} \). It is defined as follows:

  \[
  \text{var } (TL) = \frac{1}{|TS|} \sum_{i=1}^{k} \text{Dis}(P_i, \bar{P})^2
  \]  

  Where \( \bar{P} \) is the centroid of all the locations in the subset, \( \bar{P} \) is calculated as below:

  \[
  \bar{P}, \text{Lng} = \frac{\sum_{i=1}^{k} P_i, \text{Lng}}{|TS|}
  \]  

  \[
  \bar{P}, \text{Lat} = \frac{\sum_{i=1}^{k} P_i, \text{Lat}}{|TS|}
  \]  

- **Point-of-interest variance**

  Point-of-interest variance (varp) measures the variance of the set of point-of-interests \( I = \{\text{POI}_{i1}, \text{POI}_{i2}, \ldots, \text{POI}_{im}\} \), which is covered by a test location \( P_i \). The point-of-interest variance represents the distribution of point-of-interests, which is defined as follows:

  \[
  \text{var } (P_i) = \frac{1}{|I_i|} \sum_{k=1}^{|I_i|} \text{Dis}(\text{POI}_{ik}, \bar{P})^2
  \]  

  Then, the average variance of test locations subset \( \text{var } (TL) \):

  \[
  \text{var } (TL) = \frac{\sum_{i=1}^{k} \text{var } (P_i)}{|TS|}
  \]  

  - **Centroid distance**

  Centroid distance (cdis) indicates the average distance of the Centroid of tested point-of-interests \( \text{POI}_i \) with the
test location $P_i$ in test locations subset TL, which is defined as follows:
\[
cdis(TS) = \frac{1}{|TS|} \sum_{i=1}^{k} Dis(P_i, POI_i)^2
\]  
(6)

Where, the Centroid of tested point-of-interests $\overline{POI_i}$ is calculated as follows:
\[
\overline{POI_i, Lng} = \frac{\sum_{i=1}^{n} POI_{i,k}.Lng}{|I_i|}
\]  
(7)
\[
\overline{POI_i, Lat} = \frac{\sum_{i=1}^{n} POI_{i,k}.Lat}{|I_i|}
\]  
(8)

- Point-of-interest distance variance

Point-of-interest distance variance $\text{var} \, d$ measures the variance of distances between test locations $P_i$ with covered point-of-interests $I_i = \{POI_{i1}, POI_{i2}, \cdots, POI_{i_a}\}$, which is defined as follow:
\[
\text{var} \, d(P_i) = \frac{1}{|I_i|} \sum_{k=1}^{n} \left(Dis(P_i, POI_{ik})\right)^2
\]  
(9)

Then the average of distance variance of test locations subset TL is defined as follow:
\[
\text{var} \, d(TL) = \frac{\sum_{i=1}^{k} \text{var} \, d(P_i)}{|TL|}
\]  
(10)

- Point-of-interest coverage

For a test location $P_i$, a set of point-of-interests $I_i = \{POI_{i1}, POI_{i2}, \cdots, POI_{i_a}\}$ can be tested by $P_i$, which meet the relation $Dis(P_i, POI_{ik}) \leq \ell$. Here, $\ell$ is test distance. Thus, for the test location subset TL, the average point-of-interest coverage is defined as fellow:
\[
p \, \text{cov}(T) = \frac{\sum_{i=1}^{k} |I_i|}{|TS|}
\]  
(11)

IV. CASE STUDY

This section reports a case study that evaluates the effectiveness of the proposed approaches. We first present the experimental process, and then give the evaluation metrics. At last, experimental results are analyzed and discussed.

A. Experimental process

We select a mobile app “SmartTravel”, which are developed by our students. The app provides hotels, restaurants, scenic spots, and other point-of-interests according mobile user’s locations. Firstly, we generate 1600 test locations using random test method. We test the app by generated 1600 test locations, and found 48 faults in 248 test locations.

Then, we randomly generate 20 test data subsets from 1600 test locations, and then select one subset from generated 20 test data subsets using the proposed metrics separately. Finally, experimental results are analyzed and discussed.

In order to analyze the stability of the proposed approach, the size of test data set is set to 100,200,400 separately, and the same experiment are executed 5 times repeatedly.

B. Effectiveness Metric

To measure the effectiveness of the proposed approach, two metrics are proposed to evaluate the effectiveness of fault detections.

a. the rate of fault finding rank

The rate of fault finding rank (rff) means the rank ratio of selected test data subset using proposed approach in all test data subsets, which is defined as follow:
\[
rff(TL_j) = \frac{\text{rnk}(TL_j)}{|TL_j|} \times 100\
\]  
(12)

Where, all test data subsets are $TL = \{TL_1, TL_2, \cdots, TL_9\}$, $TL_j$ is the selected test data subset, and $\text{rnk}(TL_j)$ is the rank of found faults for $TL_j$.

b. The rate of fault coverage

The rate of fault coverage ($r\, \text{fn}$) means the ratio of the number of found faults by test data subset to the sum of found faults by all test data subsets, which is defined as follow:
\[
r\, \text{fn}(TL_j) = \frac{\text{fn}(TL_j)}{\text{sum}(\text{fn}(TL_j))} \times 100\
\]  
(13)

Where, $\text{fn}(TL_j)$ is the number of found faults by test data subset $TL_j$, and $\text{sum}(\text{fn}(TL_j))$ is the sum of the found faults by all test data subsets.

C. Experimental results analysis

We present the experimental results in Fig.1. We found the rff and rfn of the subsets selected by centroid distance
(cdis) is unstable, and the found fault rate is lower. So this metric is not suitable for selecting test data. Other four metrics can select suitable test data subsets, and experimental results are stable. Then the four metrics are effective for test data selection for regress testing of mobile LBS.

By comparing the four metrics, we found that point-of-interest variance and point-of-interest distance variance have similar results. And two metrics both measure distribution dispersion of the point-of-interests. Those metrics can recommend best test data subsets, and found more faults.

V. RELATED WORKS

Nowadays, mobile LBS have become one hot research topic in mobile computing domain, and many papers have been published to address different areas in mobile LBS. A conceptual framework for personalized location-based tourism apps leveraging semantic web to enhance tourism experience is proposed by Mahmood [3]. Al Nabhan presents a new strategy in achieving highly reliable and accurate position solutions fulfilling the requirements of Location-Based Services (LBS) pedestrians’ applications [8].

The location privacy issues are serious for LBS. Zhang et al. propose an LBS privacy-quantifying framework and used the mutual information metric to measure adversary’s information gain in his inference attacks [9]. An adaptive location privacy-preserving the system is presented, which allows a user to control the level of privacy disclosure with different quality of location-based services [10].

Freudiger et al. use Kullback-Leibler divergence between prior and posterior distributions to measure the ability of the adversary to guess the probability of each user visiting specific POIs [11].

However, there are a few publications about mobile LBS testing. Jerry Gao discusses the issues and difficulties of mobile LBS testing [12]. KeZhao proposes a suite of metrics for prioritizing test cases for regression testing of LBS [13]. Nigel Davies proposes a hybrid test and simulation environment for evaluating system- and network-related issues in location-based applications. Huichun Chu proposes a two-tier test approach for location-aware mobile learning systems [14]. Solveig Bjørnestad presents an example study about evaluation of a location-based mobile news reader [15]. Jiang Yu analyzes test requirements, and presents a scalable testing framework for mobile LBS [16].

We have proposed an initial test model [17] and some test coverage metrics [18] for function services of mobile LBS. In this paper, we present some test strategies about selecting test devices, location context, location objects, and moving patterns. And then the test approaches are described in details using a case study.

VI. CONCLUSION

In this paper, we propose some selection metrics for regression testing of mobile LBS. We also provide a case study to describe our test approaches in details. We hope our approaches are useful for test engineers to improve effectiveness and quality of regression testing of mobile LBS.

REFERENCES


