# Navigating and Learning with Location Based Services: A User-Centric Design

**Kai-Florian Richter[1,2], Drew Dara-Abrams[3], Martin Raubal[3]**

[1] Transregional Collaborative Research Center SFB/TR 8 Spatial Cognition,
University of Bremen, Germany
richter@sfbtr8.uni-bremen.de

[2] School of Information Sciences, University of Pittsburgh, USA

[3] Department of Geography, University of California, Santa Barbara, USA
{drew,raubal}@geog.ucsb.edu

**Abstract.** Many architectures of location based services (LBS) focus on the interplay of the involved technologies. Instead, we present a modular architecture that centers on the outcomes of LBS for users. Specifically, we derive a process-oriented context model for service adaptation and develop from this a user-centric LBS architecture that distinguishes different degrees of user involvement. This model highlights the effects that differences in interaction have for the users, for example, the effects on spatial learning. We illustrate this in an exploratory empirical investigation of interaction differences in the navigation services offered by Apple's iPhone and Google's Android smart-phones, which demonstrates how a difference in device design leads one to be more efficient for navigation and the other to be better for spatial learning.

**Keywords:** Location based services, mobile interaction, context, navigation, spatial cognition, spatial learning.

## 1 Introduction

Location based services (LBS) use positioning, telecommunication, and mobile computing technologies to deliver information and assistance to users based on their geographic position. To date, much of the emphasis in LBS development and research has focused on the first half of this equation: the numerous technologies assembled into an architecture. Consider, for example, the Open Location Services

Interface Standard[1]. OpenLS documents a set of services providing core, directory, gateway, location utility, presentation, route, navigation, and tracking functionality. But what of the second half of the LBS equation: the people who use these services?

Take the case of a middle-aged man using an in-car satellite navigation service (the most popular form of LBS these days). The fellow would like his LBS to assist him with a number of related but slightly different navigation tasks, such as generating route directions to out-of-town locations, finding alternative routes when he encounters a traffic accident along the way, and searching for a pizza parlor once he has reached his destination. All of these tasks make use of the same route, navigation, and presentation services (to use OpenLS parlance), but for each task, our user has a different goal and a different context. In the first case, he is likely at home with time to plan and with knowledge of his nearby surroundings; in the second, he is driving or pausing in a parking lot on the side of the road; and in the third, he is unfamiliar with his surroundings and likely to only briefly stop in order to interact with the service. To further complicate our story, this fellow is not the average user (the notion of an average user being an ideal). Like a significant minority of men, perhaps he is red-green color blind. When performing all of those three tasks with his LBS, he would like the color palettes used in map displays designed with his vision limitations in mind. His wife, on the other hand, prefers full-color map displays but would like the option to switch between map displays and text directions.

In this paper, we take (in Section 2) the use case of the standard navigation service (as the archetypal LBS) and consider both its *architecture* and its *outcomes*, i.e., how the everyday users of navigation services achieve (or do not achieve) their immediate and longer-term objectives. This focus on users both suggests that LBS researchers need to take into account additional factors [1] and also evaluate actual outcomes. We expand the technical architecture of LBS to include aspects relevant to the people who use LBS—namely, *context*, *task*, and *user properties*—and discuss how LBS can address these properties using *adaptive* and *adaptable services* (in Section 3). Toward the second end, we conclude with an experiment (in Section 4) in which pedestrians navigate suburban neighborhoods using smart-phone navigation services, which are rapidly replacing in-car systems. Today in 2010, the state-of-the-art smart-phones are the Apple iPhone and the Google Android, which differ in how their included navigation services pan and zoom through routes. Our experiment exploits this difference to evaluate how efficiently people can navigate routes with LBS assistance, how well they can learn those routes along the way, and how the goals of navigation performance and learning may in fact be trade-offs. The modular, user-centric architecture developed in this paper begins to suggest (in Section 5) a manner by which these trade-offs in outcomes can be taken into account as part of the overall scheme of an LBS. The designs of particular devices may change from year to year, but this

[1] http://www.opengeospatial.org/standards/ols

user-centric architecture is built on technical principles and behavioral findings of lasting relevance.

## 2 LBS and Navigation

LBS are information services that are sensitive to the location of mobile users, relate their location to the surrounding environment, and provide location based information to facilitate the successful completion of spatio-temporal tasks. Typically, LBS run on mobile devices that provide at least a positioning mechanism and a network connection. With a focus on navigation services, this section discusses LBS architecture, personalization, and use.

### *2.1 Technical Architecture of LBS*

LBS are embedded within complex technical infrastructures, including positioning systems, application servers, and mobile devices [2, 3] (Figure 1). Mobile devices receive position information and connect users to LBS. Positioning of mobile devices works either actively, such as through a GPS (Global Positioning System) receiver, or passively, i.e., the position is accessed over a network connection, such as the mobile phone network. Other technologies can be utilized for indoor positioning [4]. Wi-Fi or cell networks connect the mobile devices (the clients) to LBS providers, and the providers deliver the actual service based on the user's position.

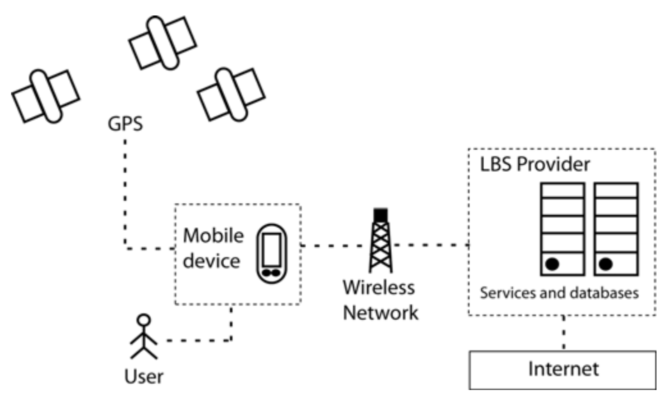



**Fig. 1.** Technical architecture of LBS with its typical components, adapted from the OpenLS specification (see footnote 1).

### *2.2 Navigation Assistance in LBS*

As with most routing services, LBS use a network representation of the environment to calculate a route from origin to a destination. Calculation may return the shortest or fastest route, or optimize routes according to other parameters, such as the most scenic or easiest route [5, 6]. Presentation of these routes has to account for the limitations of the device. This mostly affects graphical presentations due to the limited screen size, but may also consider background noise in city environments when delivering spoken text [7].

Instructions on how to follow a route may either be presented *in-advance* or *incrementally* [8]. In-advance directions present all instructions before route following starts. This is what route services on desktop computers do. Users get an overview of what to expect along a route. Incremental directions provide step-wise instructions on the next action to be performed close to each decision point. This is what LBS typically do, given the limited screen size of mobile devices.

LBS have essentially three ways to incrementally present navigation information: 1) only present local information (only give information on the next decision point to come); 2) perform automated adaptation to the currently appropriate level of detail (switch automatically between overview and detailed views); 3) let users decide on which level of detail information is presented (provide means for zooming and panning the presented information).

### *2.3 Empirical Studies on Navigation with LBS*

Several studies have investigated these and other presentation options and their effects on task performance and spatial learning in navigation with mobile devices. In these studies participants navigated an unknown environment (real or virtual) using a mobile device with an LBS. Navigation performance is measured by traveled distance, time taken, and the number of navigation errors made. Faster travel with a few deviations from the shortest path is considered to indicate successful assistance from the LBS. Often studies also look at the spatial knowledge participants acquire while using the LBS. This may test for *route knowledge*, i.e., the linear knowledge subjects have about the way they have traveled, or *survey knowledge*, i.e., the metric knowledge they have acquired about the layout of the environment [9]. Spatial knowledge can be tested by sorting images of intersections in their order of appearance along a route, by pointing tasks, or by drawing sketch maps, among other tasks. When participants score higher on these tests of spatial knowledge, it is again taken as an indication of successful assistance from the LBS.

In [10], participants navigated through a zoo using either a PDA or a head mounted clip-on. The devices incrementally displayed photos of each intersection, augmented by either graphical lines indicating the direction to be taken or verbal commands describing the action to be performed. Performance and directional knowledge were fairly good across both modalities. Participants were asked to place markers representing decision points on an empty road map as a test of their survey knowledge. This evaluation showed that survey knowledge was poor in all conditions. In another study in the same setting, participants navigated either using a PDA or printed maps [11]. The PDA had three different modes: 1) only visual information. When approaching an intersection an animation showed the relation of the previous, current and next intersection. A line on the intersection's photo then indicated the way to take. 2) The same as 1), but with the photo a verbal instruction was given. 3) Only the photo and verbal instruction. The printed maps only showed part of the environment at the same time. Results were that map users acquired much better route and survey knowledge than the PDA users. The presentation mode had no influence on the performance; animations did not help.

In [12], participants navigated in a multi-level virtual environment. They had either continuous access to a map showing their position or could request to see it at all times. In both conditions participants either had to solve location quizzes (indicate current position on map) or not. Sixteen runs were performed with assistance (a run being the task to find a specific target from the current start position) and a final transition run without any assistance. Excess distance, the number of map requests, and performance in the quizzes were used as performance measures. Participants with continuous position indication performed best with regard to excess distance. However, for those requesting a map, excess distance and number of requests decreased with increasing number of runs, indicating that learning took place. The quizzes had no immediate effect on performance, but again learning took place, as participants got better in the quizzes with increasing number of runs. For the transition run, those having had continuous position indication and no quizzes performed worst, while those requesting maps and having quizzes performed best.

Using three different groups—participants that had traveled a test route once before; participants using paper maps; and participants using a GPS-based handheld navigation system—Ishikawa et al. [13] tested the influence of assistance medium on wayfinding performance. The groups traveled six different routes; at the end of each route they had to point back to the origin. After all routes, participants drew a sketch map of the environment. Performance measures were deviation from shortest path, travel speed, number of stops, finding the goal at all, and direction estimates and sketch-map accuracy. Participants using the GPS traveled longer distances, were slower, and made more stops. Their configurational and topological understanding of the environment was worse. While the device allowed users to find their way, it was less effective than maps or direct experience as support for smooth navigation.

These studies demonstrate that using mobile navigation devices lead users to "turn off their brain." They do not process the presented information and the information perceived in the environment to a sufficient level which results in great difficulties in acquiring both route and survey knowledge. This can be attributed to a lack of attention to their surroundings, which is a common phenomenon in automation, and a focus solely on when the devices issue new instructions, which decouples the actions to be performed from their spatial embedding. The experiments in [12] show that involving users more deeply in the navigation process results in a learning effect. LBS design should aim for a way of presenting information that is useful in the given situation and also fosters processing of that information, increasing users' confidence of "doing the right thing" and decreasing their dependency on the device [14].

## 3 A Modular User-Centric Architecture for LBS

If we return to the LBS architecture discussed in Section 2.1, we find no components to account for these behavioral results. The OpenLS specification (and similar architectures) cannot help an LBS developer to understand which design characteristics will help the users of a navigation system acquire more accurate spatial knowledge, follow a route more efficiently, or reach another outcome. In this section, we present a novel architecture for LBS that is modular and user-centric.

### *3.1 Adaptation to Users, Tasks, and Context*

User-centric LBS adapt to the needs of the individual user, the demands of the given task, and the context of the particular environment [15-19]. There are two ways of achieving knowledge sharing between a service and its user: making the service adaptive or adaptable [20] (Table 1). *Adaptive services* provide dynamic adaptation to the current task and user, with little or no effort involved by the user. *Adaptable services* have the user change the functionality of the service and therefore keep the user in control.

**Table 1.** Two methods by which services can adapt to users, tasks, and context, modified from [20] and [21].

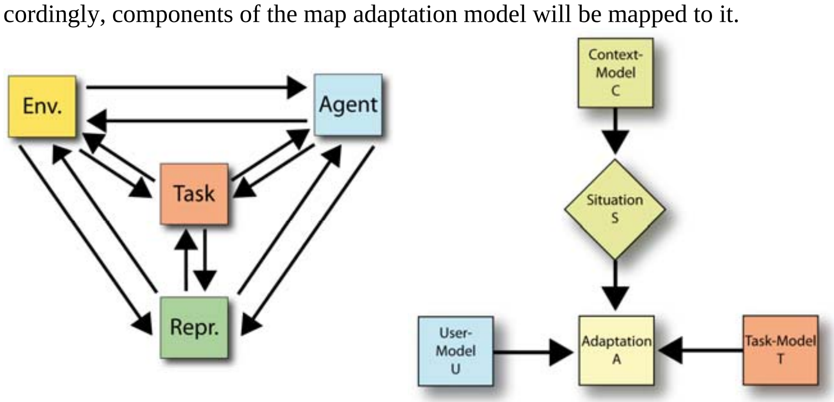
| | Adaptive | Adaptable |
|---|---|---|
| Definition | dynamic adaptation by the service to current task and user | user changes functionality of the service |
| Strengths | little (or no) effort by the user | user is in control |
| Weaknesses | loss of control | user must do substantial work |

### *3.2 Modular LBS Architecture*

In this novel user-centric architecture, the *task* is the driving force in determining the *context* of interaction of a user with the device and environment. We look at the task from the perspective of the users: What is their level of involvement in the execution of the task? What is the effect of automation on understanding the situation? How may a task be personalized?

The proposed modular architecture is based on the process-oriented context model of Freksa et al. [22] and the formal mobile map adaptation model developed in [21] (Figure 2). Combining both models results in a general model that focuses on how the current task influences interaction of a user with device and environment.

The process-oriented context model covers how an *agent* (which we have been referring to as a user) acts in an *environment* using a *representation* of that environment (in our broader LBS architecture, this is provided by the mobile device). The task determines which processes between the components environment E, agent A, and representation R become relevant. In the formal map adaptation model the task determines how adaptation may occur. When unifying the two models the emerging model allows for defining interaction with a system and environment in a user-centric way. This unification requires mapping components of one model to those of the other. The task is the central element in the process-oriented context model, which shall also be the case for the unified model. Accordingly, components of the map adaptation model will be mapped to it.




a) b)

**Fig. 2**. a) Context model as defined in [22]; b) context model developed in [21].

The *User-Model* U of Figure 2b maps to the agent A in Figure 2a. This is a direct mapping. The Task-Model T maps to the task T. The *Context-Model* C in [21] defines the current *Situation* S. This has no direct counterpart in the other model since, here, the interplay between all components—especially the processes represented by arrows in Figure 2a—determines the situations. Components of the Context-Model can be found in all elements of the process-oriented model. The representation component of the process-oriented context model captures any kind of external aid used to interact with an environment. For the purposes of the modular LBS architecture, it is generalized to represent the device with its interface properties.

Figure 3 illustrates a unified model. The task is in the center; it determines the processes between agent A, environment E, and device D as is the case in the process-oriented context model. Additionally, the task defines which adaptations in interaction with and presentation of the device are possible and sensible. Either the agent or the device performs these adaptations as part of the interaction between these two components, which goes back to the previous discussion of adaptive versus adaptable. In a subsequent step, the adaptations influence the behavior of the device (e.g., its information display); this step is not depicted in Figure 3.

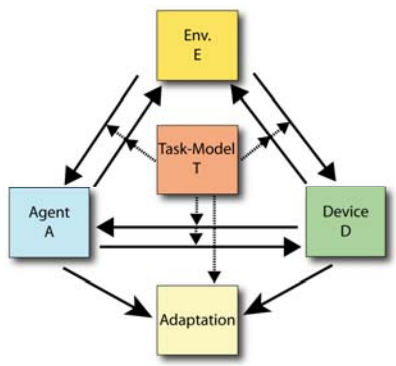



**Fig. 3.** The combined context models adapted for use with LBS.

Using the generalized context model, for different tasks within an LBS the level of user involvement for their respective parts can be identified. This makes use of the activity theory for cartography [23]. Each task is divided into activities, goals, and sub-goals. Different (combinations of) activities fulfill different sub-goals and eventually lead to the overall goal. In terms of the modular context model, each sub-goal requires a different activity, which will trigger different processes between agent and device (different interactions with the device), between agent and environment (e.g., performing a wayfinding action), or between device and environment (e.g., getting a position). Breaking down tasks to this level reveals differences in the required user involvement for successfully performing activities. It allows for a detailed view on an overall task that can be used to identify the parts of user-system interaction that are crucial to keep users globally oriented and receptive to their environment. Accounting for this when implementing LBS may avoid the effects of lack of spatial knowledge acquisition and feelings of dependency found in behavioral studies (Section 2.3).

In summary, activities may be categorized regarding the level of user involvement. There are three different levels of involvement:

Level 1. Functionality the user does not need (and want) to get involved in. In general, this comprises processes between device and environment, for example, receiving GPS signals and calculating a position.

Level 2. Functionality the user needs to be involved in to foster learning and decrease dependency on the device. These functions can only be personalized to optimize an individual's learning process, but may not be altered such that they lose their learning effect.

Level 3. Functionality that may be personalized to a specific user's preferences and needs in any conceivable way.

With this distinction, we define a modular, user-centric architecture for LBS. The major difference to existing architectures is its focus on the processes that are required to perform a task, instead of looking only at the technical components. For each activity it allows defining the required user involvement by changing the participating components of the service. Each overall task (e.g., planning a route ahead of a trip or finding alternative routes along a trip) comes with different sets of activities; each activity determines the involved components and processes between them; each process defines the level of required user involvement. This perspective focuses on the second half of the LBS equation; it facilitates changing the outcomes for the users, such as minimizing user interaction or maximizing acquisition of spatial knowledge.

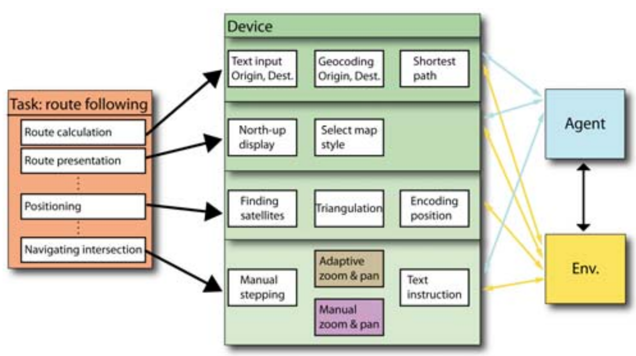



**Fig. 4.** An example of the user-centric modular architecture. The different activities also change the processes between agent and environment, which is not depicted in this simplified view. Among the many possible, the figure highlights one difference in modules that is subject of an empirical study presented in Section 4.

Figure 4 gives an example. The task "route following" is broken down in activities such as "positioning" or "navigating an intersection." Each activity involves different components of the device's modular architecture. "Positioning" is an activity that does not involve any user interaction (Level 1). The "map style" component may be adapted to a user's preferences (Level 3). The figure illustrates one particular example of a Level 2 activity: a distinction between automatic zooming and panning to the next intersection (adaptive behavior) vs. manual zooming and panning (adaptable behavior). This difference will be subject of an empirical study detailed in the next section.

## 4 Navigating with Smart-Phones: An Empirical Study

To address the effects adaptable versus adaptive LBS have on user performance and spatial learning, we conducted an empirical case study of people using smart-phone navigation services. The experiment and its results also serve to demonstrate and ground the proposed modular user-centric LBS architecture.


**Fig. 5.** a) The Apple iPhone 3GS displaying a portion of the Camino Real route; b) the Google Android G1 displaying a portion of the Storke Ranch route.

We investigated the way by which people advance through the route directions presented on the smart-phone. When a user presses an arrow button, the Apple iPhone automatically pans the map and zooms its extent to include both the beginning and end of the next route segment. At the top of the screen, the respective route instruction is displayed (e.g., "Turn right at Pacific Oaks Rd."; Figure 5a). When a user presses a similar arrow button on the Google Android, the respective route instruction is overlaid on the map, near the next decision point, but the map stays put—it is left to the user to pan and zoom (Figure 5b). The iPhone is adaptive in this respect, while the Android is adaptable.

The modular user-centric LBS architecture (in addition to the literature reviewed in Section 2) suggests that these different design characteristics will lead to different user experiences and outcomes. We predict that the iPhone's adaptive pan and zoom will lead to more efficient navigation performance, with users on average taking fewer wrong turns, and that the Android's adaptable pan and zoom will lead to greater learning, with users on average being more adept at re-walking the route without the aid of the navigation service and at conveying the spatial knowledge they acquired from manually panning and zooming the map display. That is, we expect to find a trade-off in users' navigation performance and spatial learning, with the design of the navigation system determining which system performs better in which respect.

### *4.1 Methods: Participants, Instruments, and Procedure*

Eight graduate students, staff members, and alumni from the University of California, Santa Barbara (UCSB) participated in the study (six female, two male). Only one owned a smart-phone (an older generation iPhone), which did not have a built-in GPS unit. Most participants had not visited the study neighborhoods before.

Participants began by completing a demographics questionnaire and the Santa Barbara Sense of Direction Scale, a standard self-report questionnaire measuring one's environmental-scale spatial ability [24]. Next, participants were individually taken to one of two suburban neighborhoods near the UCSB campus in Goleta, California: Storke Ranch and Camino Real (Figure 5). They were given a brief lesson in using the pedestrian navigation service on the iPhone or the Android (the order was counterbalanced). Participants received a card listing three addresses with descriptive names (e.g. Corner House, Picnic Table), they were told that the first address was for their current starting location, and they were instructed to use the smart-phone to navigate to the second address, to the third address, and then back to the first. The experimenter followed along, recording any comments made and marking any wrong turns. If participants took more than two consecutive wrong turns, the experimenter suggested they check where they were going. Both routes were approximately 1.5 miles long.

After returning to the beginning of the route, participants were instructed to re-walk the entire route. During this test phase, participants were not allowed to use the navigation service and were instead instructed to use Cognitive Surveyor [25] to track their movements using GPS and to test their spatial knowledge. At each destination, participants were instructed by this Android application to estimate the direction and distance from their location to each of the two other destinations. This is a standard measure of survey knowledge. Again, the experimenter followed, recorded any wrong turns, and informed participants if they had taken more than two wrong turns in a row. The number of wrong turns is a standard measure of route knowledge.

After completing the test phase of the first route, participants were taken to the beginning of the second route, in the other neighborhood. They were then given the smart-phone they did not use in the first route, and asked to repeat the process of the learning phase and the test phase. Finally, participants completed a questionnaire asking about their experiences using the two different smart-phones and they were debriefed on the reasons behind the experiment.

### *4.2 Results and Discussion*

Let us discuss the experiment's results using the terminology of the user-centric modular LBS architecture. Eight users participated in the study, each with a different level of spatial ability, as measured by the Santa Barbara Sense of Direction Scale[2]. They completed two different tasks: use the LBS to navigate—and unknowingly learn—an unfamiliar route and re-walk the route from memory. They performed these tasks in two environments (the Camino Real neighborhood with a somewhat rectilinear grid and the Storke Ranch neighborhood with curving streets and cul-de-sacs) using two different devices (the iPhone with adaptive/automatic panning and zooming and the Android with adaptable/manual panning and zooming). In total, the routes were walked 32 times.

Participants' performance on the navigation-with-LBS task was measured by the number of wrong turns while first walking a route. Their spatial learning was measured by the number of wrong turns each made while re-walking the route (a measure of route knowledge) and by their accuracy at estimating the directions and distances between the destination points (a measure of survey knowledge).

A factorial analysis of variance (ANOVA) of the wrong-turn data shows no main effects. None of the factors (device, task, and environment) made a significant difference on its own in the mean number of wrong turns made by a participant. However, there is a significant three-way interaction, $F(4, 32) = 3.261$, $p = .029$, implying that the number of wrong turns made by participants depended upon the combination of device, task, and environment. Figure 6a shows that participants using the iPhone made more wrong turns while performing the test task, while participants using the Android made more wrong turns while performing the learning task. This is evidence for our prediction that the design of an LBS leads to trade-offs in outcomes.

[2] Note that this number of participants may be sufficient for drawing preliminary conclusions here but that a larger number will be required for more rigorous follow-up.

As shown in Figure 6b, participants showed different patterns of results in the two different environments. Android users took their wrong turns on the curving streets of Storke Ranch, while iPhone users took wrong turns in both neighborhoods (on different tasks). This may be explained by one participant's comment that on the Camino Real route, she chose to leave the Android view set to its default, maximum extent, which encompassed the entire route. She was able to navigate the entire route without panning or zooming. Future studies should more carefully control for the level of difficulty of the test environments, but for the purposes of this exploratory experiment, it's actually interesting to see how the environment is another factor that interacts with device and task properties to shape outcomes.

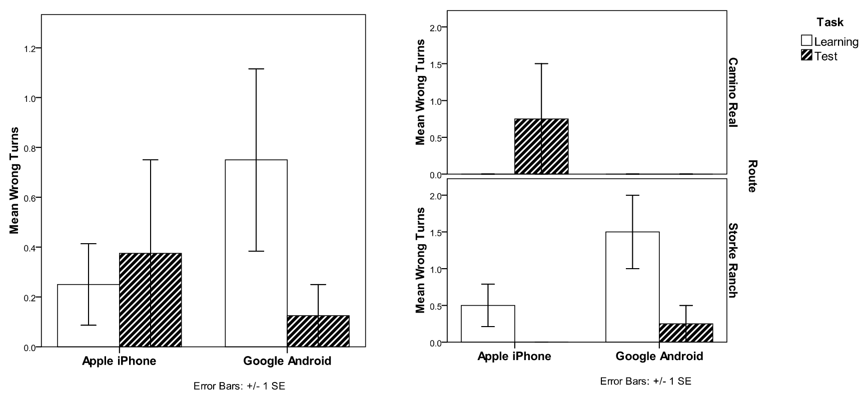



**Fig. 6**. A measure of route knowledge: a) Mean number of wrong turns made by participants aggregated across the two routes; b) split by route.

The fact that users could choose to squeeze the entire route onto the Android screen may also have affected the test of survey knowledge. The iPhone can do the same, but since participants were not allowed to manually manipulate the map scale or extent, they could not do so. The accuracy of participants' direction estimates between destinations did not significantly differ from those who learned on the iPhone and those who learned on the Android. But accuracy of distance estimates did significantly differ, $t(14) = .566$, $p = .042$, with Android users showing, on average, .07 miles less error in their distance estimates. This is approximately 29% of the average distance between destinations. Since they were allowed to pan and zoom the map as they wished (sometimes to the entire extent, as the participant just mentioned did), participants using the Android appear to have acquired more accurate distance knowledge. This finding is in line with recent studies of spatial learning from small, mobile map displays and from large, standard paper maps, which suggest more accurate spatial learning when less panning and zooming is required [26, 27].

The user property of spatial ability did not predict the number of wrong turns made by participants or the accuracy of their distance knowledge. It did marginally correlate with errors in their direction knowledge, $r(16) = -.462$, $p = .071$. Participants with higher scores on the Santa Barbara Sense of Direction Scale were more accurate estimating directions from one destination to another.

Another pattern emerged with respect to screen orientation. At least half of the participants were observed physically rotating the iPhone and the Android so that the directions on the on-screen map were aligned with those of their surroundings. Many said that they would like the phone to automatically rotate the display (a *track-up map display*, as opposed to the standard *north-up map display*). In the future, a similar study could be performed to test whether an adaptive interface in which the track-up map automatically rotates leads to better navigation performance and worse spatial learning than the current north-up maps, which are adaptable in that the user can physically rotate the phone. Previous research has shown a similar trade-off in airplane pilots using cockpit displays [28].

The results of this study, focusing in particular on panning and zooming map displays, show how device, user, environment, and task factors interact to affect navigation performance and spatial learning outcomes.

## 5 Trade-offs in LBS Architectures and Outcomes

According to the standard LBS architecture reviewed in Section 2, there are no important differences between using the navigation services on the iPhone and the Android. The overall technical infrastructure is the same; it is only a slight difference in the presentation on the device. Our empirical study suggests that this slight but key difference actually makes a noticeable impact when the scope of the LBS architecture is expanded to include users, their environmental context, and their tasks. Whether the device is adaptable or adaptive will lead to certain trade-offs in outcomes. In this paper, we have presented an exploratory study focusing on navigation services and the particular design characteristic of panning and zooming in the context of pedestrian travel through suburban neighborhoods. Yet the experimental methodology and the modular user-centric LBS architecture developed here are of more general use. This is true both for other components of today's mobile navigation services (e.g., north-up vs. track-up map displays; graphical vs. textual route instructions) that influence understanding and learning, as well as for future developments in LBS principles and technology. As LBS become available to a wider range of people around the world, this need to shift the focus from technological infrastructure to the needs, contexts, and tasks of the user will become even more important.

**Acknowledgments.** K.-F. Richter's work has been partly supported by the SFB/TR 8 Spatial Cognition, which is funded by the Deutsche Forschungsgemeinschaft (DFG), and partly by the

School of Information Sciences, University of Pittsburgh. D. Dara-Abrams's work is supported by the U.S. National Science Foundation, through a Graduate Research Fellowship and the Interactive Digital Multimedia IGERT (grant no. DGE-0221713). Thanks to Mike LeBeau of Google for Android devices.

## References

1. Reichenbacher, T., *Adaption in mobile and ubiquitous cartography*, in *Multimedia Cartography*, W. Cartwight, M. Peterson, and G. Gartner, Editors. 2007, Springer: Heidelberg. p. 383-397.
2. Küpper, A., *Location-Based Services - Fundamentals And Operation*. 2005, Chichester, England: Wiley. 365.
3. Brimicombe, A. and B. Li, *Location-Based Services and Geo-Information Engineering*. Mastering GIS: Technology, Applications & Management. 2009, Chichester, UK: Wiley-Blackwell.
4. Kolodziej, K. and J. Hjelm, *Local Positioning Systems: LBS Applications and Services*. 2006: CRC Press.
5. Golledge, R., *Path Selection and Route Preference in Human Navigation: A Progress Report*, in *Spatial Information Theory-A Theoretical Basis for GIS*, A. Frank and W. Kuhn, Editors. 1995, Springer: Berlin-Heidelberg-New York. p. 207-222.
6. Richter, K.-F. and M. Duckham, *Simplest instructions: Finding easy-to-describe routes for navigation*, in *Geographic Information Science - 5th International Conference, GIScience 2008*, T. Cova, et al., Editors. 2008, Springer: Berlin. p. 274-289.
7. Kray, C., et al. *Presenting route instructions on mobile devices*. in *International Conference on Intelligent User Interfaces (IUI'03)*. 2003: ACM Press.
8. Richter, K.-F., *Context-Specific Route Directions - Generation of Cognitively Motivated Wayfinding Instructions*. Volume DisKi 314 / SFB/TR 8 Monographs. Vol. 3. 2008, Amsterdam, The Netherlands: IOS Press.
9. Siegel, A. and S. White, *The development of spatial representation of large-scale environments*, in *Advances in Child Development and Behavior*, H. Reese, Editor. 1975, New York: Academic Press. p. 10-55.
10. Krüger, A., et al. *The Connected User Interface: Realizing a Personal Situated Navigation Service*. in *IUI 2004*. 2004. Madeira, Funchal, Portugal: ACM Press.
11. Münzer, S., et al., *Computer-assisted navigation and the acquisition of route and survey knowledge.* Journal of Environmental Psychology, 2006. **26**: p. 300–308.
12. Parush, A., S. Ahuvia, and I. Erev, *Degradation in Spatial Knowledge Acquisition When Using Navigation Systems*, in *Spatial Information Theory - 8th International Conference, COSIT 2007, Melbourne, Australia, September 2007*, S. Winter, et al., Editors. 2007, Springer: Berlin. p. 238-254.
13. Ishikawa, T., et al., *Wayfinding with a GPS-based mobile navigation system: A comparison with maps and direct experience.* Journal of Environmental Psychology, 2008. **28**: p. 74–82.

14. Willis, K., et al., *A comparison of spatial knowledge acquisition with maps and mobile maps.* Computers, Environment and Urban Systems, 2009. **33**(2): p. 100–110.
15. Li, C. and P. Longley, *A Test Environment for Location-Based Services Applications.* Transactions in GIS, 2006. **10**(1): p. 43-61.
16. Dey, A. and G. Abowd, *Towards a Better Understanding of Context and Context-Awareness*, in *CHI 2000 Workshop on the What, Who, Where, When, Why and How of Context-Awareness*. 2000: The Hague, The Netherlands.
17. Raubal, M., *Cognitive Engineering for Geographic Information Science.* Geography Compass, 2009. **3**(3): p. 1087–1104.
18. Davies, N., et al., *Using and Determining Location in a Context-Sensitive Tour Guide.* IEEE Computer, 2001. **34**(8): p. 35--41.
19. Byun, H. and K. Cheverst, *Exploiting user models and context-awareness to support personal daily activities*, in *Proceedings of the workshop on user modelling for context-aware applications (UM '2001)*. 2001: Germany.
20. Fischer, G., *Shared knowledge in cooperative problem-solving systems - integrating adaptive and adaptable components*, in *Adaptive user interfaces: Principles and practice*, M. Schneider-Hufschmidt, T. Kühme, and U. Malinowski, Editors. 1993, North-Holland: Amsterdam. p. 49–68.
21. Raubal, M. and I. Panov, *A Formal Model for Mobile Map Adaptation*, in *Location Based Services and TeleCartography II - From Sensor Fusion to Context Models. Selected Papers from the 5th International Symposium on LBS & TeleCartography 2008, Salzburg, Austria*, G. Gartner and K. Rehrl, Editors. 2009, Springer: Berlin. p. 11-34.
22. Freksa, C., A. Klippel, and S. Winter. *A cognitive perspective on spatial context*. in *Spatial cognition: Specialization and integration, Volume 05491 of Dagstuhl Seminar Proceedings*. 2007. Dagstuhl, Germany.
23. Dransch, D., *Handlungsorientierte Mensch-Computer-Interaktion für die kartographische Informationsverarbeitung in Geo-informationssystemen*. 2002: Fachbereich Geowissenschaften, Freie Universität Berlin.
24. Hegarty, M., et al., *Development of a Self-Report Measure of Environmental Spatial Ability.* Intelligence, 2002. **30**: p. 425-447.
25. Dara-Abrams, D., *Cognitive surveying: A framework for mobile data collection, analysis, and visualization of spatial knowledge and navigation practices*, in *Spatial Cognition VI - Learning, Reasoning, and Talking about Space. Proceedings of the International Conference Spatial Cognition 2008, Freiburg, Germany*, C. Freksa, et al., Editors. 2008, Springer: Berlin. p. 138-153.
26. Dillemuth, J., *Navigation tasks with small-display maps: The sum of the parts does not equal the whole.* Cartographica, 2009. **44**: p. 187-200.
27. Gartner, G. and W. Hiller, *Impact of restricted display size on spatial knowledge acquisition in the context of pedestrian navigation*, in *Location Based Services and TeleCartography II*, G. Gartner and K. Rehrl, Editors. 2009, Springer: Berlin. p. 155-166.
28. Aretz, A., *The design of electronic map displays.* Human Factors, 1991. **33**: p. 85-101.