An evaluation method for location-based mobile learning based on spatio-temporal analysis of learner trajectories

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ABSTRACT

The evaluation of location-based mobile learning (LBML) concepts and technologies is typically performed using methods known from classical usability engineering, such as questionnaires or interviews. In this paper, we argue that many problems that may occur during LBML become apparent in the learner's spatio-temporal behavior (i.e., her trajectory). We systematically explore how location tracking and spatial analyses can be used for the evaluation of LBML. Examples with trajectories recorded during a real learning session are presented.

Author Keywords

Location-based mobile learning, trajectory analysis, learning evaluation

ACM Classification Keywords

Collaborative learning, computer-assisted instruction, computer-managed instruction, information systems education

MOTIVATION

The positioning and multimedia capabilities of current mobile devices have given rise to novel learning paradigms that integrate the learner's position in the didactical concept, thus enhancing learning by the discovery of phenomena in situ. We refer to this kind of learning as *location-based mobile learning* (LBML) [1]. Integrated LBML management systems, such as the one presented in [2] support the teacher in developing LBML lessons, as well as in the easy dissemination of these lessons to the learners' devices. At the same time, the LBML management system stores content created by learners on a server, such as geo-tagged photos or textual answers, thus enabling the teacher to track the learning progress and provide individual feedback.

Challenges, however, still exist when using such LBML platforms [3]. These are mainly caused by environmental variability, unreliable technology, low usability, and by the learners' and teachers' background and capabilities. A careful investigation and evaluation of LBML concepts and platforms is necessary to cope with these challenges. It is clear that evaluating only the learning results is not sufficient to explain problems that might occur.

Along with the explicitly collected data, also implicit behavior data, such as trajectories measured using the Global Positioning System (GPS), can easily be logged with an LBML infrastructure. In general, the broad dissemination of mobile devices has resulted in large amounts of such location tracking data. These trajectories, also called geospatial lifelines or continuous paths in space and time, are represented as a series of observations and consist of at least a triple of ID, location, and time [4]. Such trajectories are calling for systematic research and for the development of new computing technologies for storage, pre-processing, retrieving, and mining of trajectory data and exploring its broad application [5].

This work-in-progress paper systematically explores the opportunities of analysing learners' trajectories for the evaluation of LBML concepts and platforms. We suggest that LBML platforms should provide tools that support the visual and quantitative analysis of trajectory data. Through spatio-temporal analyses, teachers could then evaluate the track(s) taken by learners to identify problems, such as getting lost, time issues, visiting incorrect places, or visiting places in an order not intended by the teacher. The relation between spatio-temporal events in the trajectories and the success in completing learning units may help to understand LBML mechanisms. In this way, teachers could use such information to improve the tasks with respect to the learning goals. We demonstrate this approach with example tracks from students who executed a sequence of LBML tasks.

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The following section reviews related work on the evaluation of LBML and trajectory analysis. The section after the review describes how trajectory analyses can contribute to the evaluation of LBML, as well as privacy issues. The paper finally concludes the findings with a discussion and outlook.

RELATED WORK

Evaluation of LBML

Vavuola and Sharples proposed six challenges in evaluating mobile learning [6]: capturing and analysing learning in context and across contexts, measuring mobile learning processes and outcomes, respecting learner/participant privacy, assessing mobile technology utility and usability, considering the wider organisational and socio-cultural context of learning, and assessing (in)formality. We will discuss in the final section how the method proposed in this paper helps to approach these challenges.

Several researchers have reported results of user evaluations of LBML, typically using methods known from classical usability engineering: Naismith et al. [7], for instance, describe their work with a complete context-aware educational resource system for outdoor tourist sites and educational centres (CAERUS) which was evaluated by a short questionnaire followed by a semi-structured interview on users' experiences. Another study was performed by [8] on the augmented reality game "Environmental Detectives", simulating a toxic spill for which students had to find the source. This study was evaluated through each team presenting their findings in front of the class, as well as through cross-team interviews and written short reports. A different evaluation approach was chosen by [9] who evaluated the "Augmenting the Visitor Experience" project through direct observation by the researchers and an analysis of in-field video diaries. Summarising, most evaluations of LBML were performed through questionnaires, interviews, or by evaluating the learning results. However, these evaluation methods require high effort and feedback to the learner has been hardly provided instantaneously.

A specific group of LBML approaches targets the improvement of students' spatial skills, such as understanding cartographic maps, improving orientation and wayfinding, or general spatial thinking. One example by [10], found in a study using a navigation game (Ori-Gami) that the interaction with the map was more intense (more touches) for children who made more errors in orientation and wayfinding. Those errors, as well as the average distance and speed, were determined by analysing GPS tracks. In this paper, we argue that spatio-temporal analyses can also help to evaluate LBML with learning objectives different from spatial thinking. The Ori-Gami example underlines the necessity to integrate spatio-temporal analysis functionality into LBML platforms.

Trajectory analysis of moving objects

Many scientists have conducted research on the physical activity and movement of human beings. Trajectory analysis has found particular interest in the fields of geographic data mining and wayfinding. Often, their goal is to understand the decision making processes, interests and activities of individual persons or crowds.

Andrienko et al. [11] identified three different types of movement data and related analysis tasks: movements of a single object (e.g., one pedestrian's navigation from A to B), movements of multiple unrelated objects (e.g., the daily commuting behavior of all inhabitants of one city), and movements of multiple related objects (e.g., an animal herd looking for food). The typical analysis goals, tasks, and methods for these three types differ, and most of the papers found in literature fall into exactly one of the three categories. We will use this categorization throughout our paper.

For the movement of a single object, [12] describe the following typical analysis tasks: extracting significant places, times and durations of visits, typical trips, their times and durations, deviations, and their reasons. They distinguish between single events and trajectories (temporally ordered sequences of positions). For multiple unrelated objects [13] introduce the following analysis tasks: 1) studies of space use, accessibility, permeability, connectivity, major flows, typical routes between places, and 2) studies of emerging patterns of collective movement: concentration/dispersion, convergence/divergence, and propagation of movement characteristics. In our work, we consider a variety of spatio-temporal properties of both, single trajectories and multiple trajectories.

Several approaches for spatial analyses of photo collections have been considered by [14]. Geo-tagged photos comprise a particularly interesting data source because, in addition to the photographer's position, his or her object of interest can also be extracted from the data [15]. Photo tasks are common in LBML since they encourage learners to explore their environment and direct their attention to the real-world phenomena of interest. By uploading these photos to a server a (geo-referenced) collection becomes available for analysis. Attractions of interest to tourists were identified by [16] with different profiles who were visiting a tourist destination such as Hong Kong. Tourist managers are interested in what locations are preferred by different groups of tourists and what travel routes they are likely to take when visiting different locations. The authors presented a method for constructing a travel dataset from geotagged photos on Flickr (popular websites for sharing photos). A dataset containing thousands of photos with temporal and geographic information attached enabled them to capture the movement trajectories of tourists on a larger scale. Two techniques, a density-based clustering algorithm (P-DBSCAN) and Markov chains, were used to mine travel behavior patterns from this dataset.

In addition, the third type of movement analysis – the analysis of relative movement of related objects (approaching, encountering, following, evading, etc.) – has been investigated. For instance, the RElative MOtion (REMO) approach proposed by [17] targets the analysis of motion based on geospatial lifelines of related moving objects. Motion patterns help to answer questions, such as the identification of an alpha animal in a pack of GPS-collared wolves, or the detection of strategic and game-play behavior of two football teams, where the trajectories of 22 players were recorded with a sampling rate of 1 second. The basic idea of the analysis is to compare the motion attributes of point objects over space and time, and thus to relate one object's motion to the motion of all others.

ANALYSING LEARNERS' TRAJECTORIES

As described in the previous section, we structure the following discussion based on the classification of movement analysis tasks by Andrienko & Andrienko [18]: analysis of the movement of single learners, analysis of the movement of multiple unrelated learners, and analysis of the movement of multiple related learners, i.e., learners moving in a group.

The distinction between single users and group users plays an important role for LBML: single users learn alone and independently, and traverse the learning area on their own. If a teacher is involved in the LBML process, information sharing happens indirectly and delayed. Because phenomena perceived during the LBML process crucially contribute to a holistic understanding of the learning content, a single user might have difficulties to classify an impression as important or unimportant due to missing second opinions. Furthermore, it can be boring to fulfill vastly interactive location-based tasks alone. In this way, free exploration is highly constructivist and might increase motivation more than executing a learning module along a predefined path.

In contrast, group users interact with each other and must take decisions together. Thus, group users can obtain social competence while finding solutions within a debate by compromise or by assertiveness. Often, self-assertive individuals try to act as map leaders. In contrast, other group members risk becoming followers by avoiding conflicts and by evading group decision-making. One advantage of groups is the direct and immediate share of impressions, which might contribute to the holistic understanding of the learning content. Groups may be put together randomly or based on common intrinsic or extrinsic motivational factors.

In the following, we describe how to apply spatio-temporal analysis to learners' trajectories. In addition, we discuss in how far spatio-temporal analysis might be useful to evaluate LBML classes post-hoc. Examples are mainly taken from an LBML project for architecture students at university level by [2].

Movement of single learners

Two types of location tracking can be found in LBML projects and the type of tracking significantly influences the kind of analysis that can reasonably be applied:

Seamless tracking, as done by a GPS logger, is typically implemented as a background service recording location data at a regular frequency, often chosen between one and several seconds. Sometimes, seamless tracking is considered as too privacy offending, too battery straining, or simply not possible due to missing hardware capabilities. In these cases, an alternative approach to location tracking consists in recording a position every time a specific function is called, such as when taking a picture [16] or solving a task. While the recording frequency of function-dependent location tracking is typically much lower, additional (task-related) data are recorded which can help in the semantic interpretation of the track point, i.e., finding the reason for the stop. The two tracking methods can also be combined.

The logged data consist of information about location and time, from which additional spatio-temporal characteristics can be derived, depending on the recording rate (e.g., speed, acceleration, curviness, curvature, sinuosity, etc. [19]). These can be indicators for the reasons why decisions were made. Obviously, the higher the recording rate, the more valid conclusions can be drawn.

For instance, acceleration or deceleration could provide evidence of the learner's uncertainty, time pressure, or (missing) motivation. This, however, may be dependent on the learner's social and cultural background. Another indicator for uncertainty could be a "zig-zag" path which could mean that the learner had problems finding the target or understanding the map [10]. However, in cases where exploration of the environment is part of the intended learning behavior, a "zig-zag" path is part of envisioned location-based learning. By correlating the path with spatial knowledge about the area, intended "zig-zag" or decelerations can be distinguished from those indicating problems.

Often the teacher expects learners to follow a certain path and to take a certain means of transportation. In that case, a spatial analysis can reveal deviations from that path, or transportation mode respectively, for which several reasons may exist: wayfinding problems (see above), changes in the environment (e.g., a construction site or flooded area), unclear communication on the path to take, or physical activity avoidance behavior. For identifying the reason additional sources need to be used (including simply asking the student). A challenge, however, consists in determining whether learners who stayed on the intended path did really perceive the real-world phenomena the teacher expected them to pay attention to.

As an example, Figure 1 shows a seamless track of one individual person who was supposed to visit as many shows and species as possible in the zoo in Nuremberg (Germany) within a four hour time limit. The trajectory in this case allows the teacher to investigate places in which the learner was moving rather fast, showing less interest in certain species (e.g., close to the lakes in the South), and which species or shows he spent more time with. In the example, the subject has visited the majority of the available shows, thus fulfilling at least part two of the learning goal. Analysing very carefully, the tracks also reveal stops when the visitor interrupted the task to eat, drink, or rest. Such information can be valuable to estimate the time a teacher should plan for the task. Thus, the evaluation of seamless tracking paths can provide helpful information for the improvement of lessons.

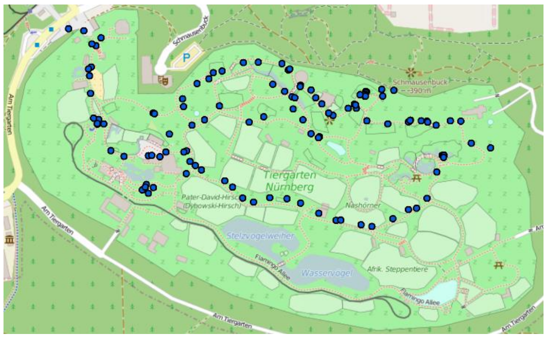

Figure 1. Learner exploring the zoo in Nuremberg (basemap: © OpenStreetMap).

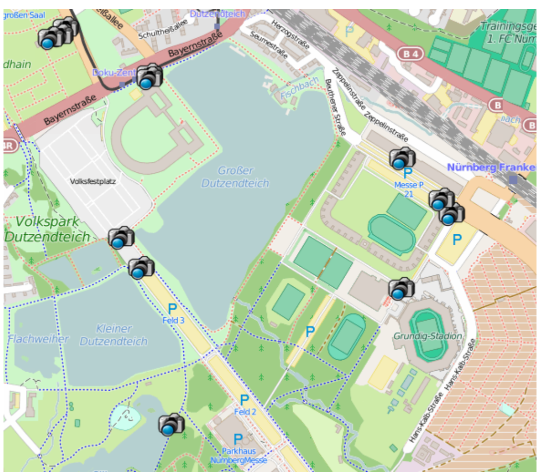

Figure 2. Recorded track on the Former Nazi Party Rally Grounds, Nuremberg, Germany (today a museum site) (basemap: © OpenStreetMap).

Another example is displayed in Figure 2. After a theoretical introduction in the classroom, a single learner had to find ten architectural buildings belonging to the "Third Reich architecture" and capture the coordinates, one representative photo, and a current usage description for each of them. Here, the learner has indeed found ten relevant buildings, but a different set than the teacher had expected. The new content can now be included into the theoretical introduction and/or the task for the next session.

Besides the improvement of lessons, the analysis of a single learner's track also enables the teacher to provide individualized help to that specific learner.

Movements of multiple unrelated learners

LBML platforms enable learners to execute the learning unit individually, i.e., outside of a formal classroom setting and in a time window of their choice. In this case, the trajectories learners take are independent from each other, while still based on the same tasks. Logging the movement data of these independent learners can lead to a, possibly large, collection of trajectories that allows for a number of analysis tasks.

First, all trajectory properties that can be analysed for an individual user (section *Movement of single learners*) can now be investigated in an aggregated form, such as: which locations did most learners find interesting (detection of Points of Interest, POI)? Where did most wayfinding problems occur? etc. Even more than for single user analyses, the results can be used to improve the LBML lessons. Methods for this kind of aggregated analyses, such as POI detection, are well-known in the literature (e.g., spatial clustering and visual analytics as described in [12]).

Second, a large dataset of trajectories can help identify users who showed similar movement (e.g., [20]) and, based on these similarities, detect clusters. The clusters can then be analysed w.r.t. the demographic, social, cultural, and other information available for the participants. For instance, we may find that females, on average, solved the task at hand in a similar way, and different to average male learners. Moreover, the paths learners took in a free-exploration task could be correlated with information on the learning effect, leading to a change in the LBML unit design.

Movements of multiple related learners

Learning can also occur within a team that pursuits the same target. Several studies have shown that the motivation rises when working with peers [21]. Knowledge can be exchanged and the constructivist learning rises as well on the condition that interaction by discussion between the learners is frequent. Each group member contributes to the team's success by occupying a specific role. However, social competence plays an important part. Consequently, the movement patterns differ between the roles occupied. The trendsetter motion pattern was introduced by [17] as one trend-setting moving point object that anticipates the motion of n others with the REMO approach. Once a trendsetter has been detected as leader, the other group members act as followers. Followers can indeed be interested in the LBML process and consequently like to adapt the leader's behavior. However, other followers prefer to evade the responsibility of contributing to the group's success. One assumption can be that interested or engaged learners are always sited close to the leader, moving at the same speed along the route. In contrast, uninterested people are located more distant to the group leader. Consequently, the speed pattern may provide evidence for distinguishing between interested and uninterested learners. Repeating outdoor learning units with the same group of learners could support these indications. However, in order to evaluate or interpret such observations it is required that the location accuracy is always known and taken into account. Another evaluation can be made by investigating the size of the group. Are the moving learners close together in a small clustered group or are they dispersing over time when they join a larger group?

In addition to the trendsetter motion pattern, [17] described two more patterns. On the one hand, the concurrence motion pattern shows cutting trajectories, which occur because individuals are pursuing their own objectives. This situation might happen after an unpredicted phenomenon, such as an accident. On the other hand, the constant motion pattern shows non-cutting trajectories, which occur because the individuals share a sequence of equal motion attributes for r consecutive time steps.

Privacy

The opportunities to improve the understanding of human behavior in its environmental context were highlighted by [22] but at the same time they warned of the potential breach of confidentiality statements made during data collection. In the case of LBML platforms, privacy issues are, first of all, the same issues as for (non location-based, non-mobile) e-learning [23]. For instance, when solving tasks in an e-learning management system (eLMS) over the web, the learner needs to trust all parties who get access to her data, which includes at least the eLMS provider and the teacher. It is plausible to simply assume a trustful teacher-student relationship, since otherwise learning would be seriously hampered. For the eLMS provider (in our case: the LBML management system provider) we suggest to choose a trustworthy party, such as the educational institution.

However, assuming that location privacy is exactly the same as general online privacy is not completely correct [24]. With data mining techniques it is possible to identify real persons based on their trajectory, even if the user is anonymized with a pseudonym [25] based on the detection of frequently visited locations (home, work, etc.) and profiles created from other data sources. The movement behavior shown during LBML, however, is usually not related to the daily routines or interests of the individual, but determined either by the pre-defined path, or by the set of locations available in the area of the learning unit. In other words, deanonymization will be difficult because all learners visit (more or less) the same set of locations.

More nuanced license models were pinpointed by [26] as another possible solution: while existing data licenses focus on property rights, it would often be more adequate to have licenses only for data usage which disallow specific kinds of harmful use or processing.

DISCUSSION AND OUTLOOK

In this paper we have systematically explored how spatio-temporal analyses of location-based mobile learners' data can be used to evaluate and improve LBML concepts and technologies. Although our method enables new types of evaluations for LBML, it is clear that the method needs to be combined with classical evaluation approaches, such as questionnaires or interviews.

As described in *Evaluation of LBML*, six major challenges for the evaluation of LBML have been identified by [6]. The method proposed here contributes to these challenges as follows:

Capturing and analysing learning in context and across contexts: location is recognized as one of the most important – if not the most important form of context. By tracking location during learning, we enable the analysis of learning behavior, strategies and success in relation to specific locations, as well as across locations.

Measuring mobile learning processes and outcomes: learning processes in LBML almost always include locomotion. Perceiving, reasoning about, and understanding environmental phenomena happens at locations, as well as during locomotion between locations. A learner's trajectory thus reflects the progress and individual development of the learning process.

Respecting learner/participant privacy: as discussed in the section *Privacy*, LBML is not more privacy-breaching than other eLMS. However, regulatory approaches to privacy need to be respected by LBML platforms which are summarized by the five principles of fair information practices in [27]. They point out that various types of inferences of movement patterns make anonymity and pseudonymity much harder to maintain than in other privacy applications, such as the Internet. Because information about personal location is highly dynamic, the potential uses and privacy implications of dynamic location information change over time. Finally they caution that without proper protection, the location information generated by location-aware systems could conceivably be abused or unfairly used in almost any domain of human, social, or economic activity.

Assessing mobile technology utility and usability: trajectory analyses can show whether learners get lost, thus revealing problems with the navigation assistance of the system (e.g., the map design). Also, systematic positioning errors become apparent in the trajectories, such as urban canyons shadowing the GPS signal in certain areas, which means a different type of positioning technology could become necessary for that specific region.

Considering the wider organizational and socio-cultural context of learning: the social context of learning could be detected if an analysis of movement dynamics within a learning group can be performed. We also mentioned that correlations between the socio-cultural context and typical movement patterns can be detected through cluster analyses based on large collections of trajectory data.

Assessing (in)formality: learning in LBML can take place at any time, independent from a formal classroom setting. This informal setting could lead to students not visiting the places they are supposed to. As explained in the section *Movement* *of single learners*, such deviations from a pre-defined path can be detected in trajectories.

One of the curriculum goals of e-learning in school education is to provide learners with 21st century skills. Kong et al. [28] anticipated a growing trend towards more individualized and collaborative learning in school education. While physical classrooms will keep their importance in learners' interaction and socialization, learning will extend to outside classrooms and play an increasingly important role in learners' knowledge construction through their daily learning activities. LBML platforms enable these learning styles, while at the same time fostering mobile technology skills, as well as orientation and navigation skills.

A delicate discussion issue is the direct derivation of the learning effect from the processed track. On the one hand, tracks can reveal a behavior; however, this behavior does not have to be based on specific impressions at a given spatio-temporal location. Because learning is influenced by feelings and impressions are perceived individually, it is not possible to state learning effects based on processed tracks only.

Furthermore, teachers should reflect how they deal with mistakes. Even if location-based problems might have been solved incorrectly, this failure does not automatically testify a lacking spatial comprehension. It might be that these failing learners did not perceive the same as the teacher did in advance to determine the correct answer. In this way, teachers must be careful and reflect the task validity to broaden the horizon of correct answers by the consideration of different perceptions. Situations might occur in which learners are able to construct truthful mental models without staying on the path suggested by the teacher, however, built with impressions unknown to the teacher. Thus, the validity of location-based tasks should be reflected in favor of constructivist knowledge acquisition.

Nevertheless, exploring the target area during preparation is essential to determine possible obstacles and to gain routine with the conduction of LBML. Consequently, teachers can get an idea about impressions perceived by the learners; this supports the creation of meshing learning goals and tasks for the LBML unit [29].

Broad studies for each presented movement category are considered right now and in future research. We will address peers across disciplines and demography as well as social and cultural origin to generate profound knowledge about LBML.

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