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Map-based Visual Analytics of Moving Learners

Christian Sailer, Institute of Cartography and Geoinformation, ETH Zurich, Zurich, Switzerland
Peter Kiefer, Institute of Cartography and Geoinformation, ETH Zurich, Zurich, Switzerland
Joram Schito, Institute of Cartography and Geoinformation, ETH Zurich, Zurich, Switzerland
Martin Raubal, Institute of Cartography and Geoinformation, ETH Zurich, Zurich, Switzerland

ABSTRACT

Location-based mobile learning (LBML) is a type of mobile learning in which the learning content is related to the location of the learner. The evaluation of LBML concepts and technologies is typically performed using methods known from classical usability engineering, such as questionnaires or interviews. In this paper, the authors argue for applying visual analytics to spatial and spatio-temporal visualizations of learners' trajectories for evaluating LBML. Visual analytics supports the detection and interpretation of spatio-temporal patterns and irregularities in both, single learners' as well as multiple learners' trajectories, thus revealing learners' typical behavior patterns and potential problems with the LBML software, hardware, the didactical concept, or the spatial and temporal embedding of the content.

KEYWORDS

Collaborative Learning, Computer-Assisted Instruction, Computer-Managed Instruction, Information Systems Education, Learning Evaluation, Location-based Mobile Learning, Trajectory Analysis, Visual Analytics

INTRODUCTION AND 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 through the discovery of phenomena in situ. We refer to this kind of learning as *location-based mobile learning* (LBML) (Brown et al., 2010). Integrated LBML management systems, such as the one presented in Sailer, Kiefer, and Raubal (2015), support the teacher in developing LBML lessons, as well as in the straightforward dissemination of these lessons to the learners' devices. At the same time, the LBML management system stores the 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. Teachers would like to be aware of the learners' behavior and difficulties in executing the outdoor exercise. These difficulties are mainly caused by environmental variability, unreliable technology, low usability of the system, and by the learners' and teachers' background and capabilities (Sailer, Schito, Kiefer, & Raubal, 2015). A careful investigation and evaluation of LBML concepts and platforms is necessary to cope with these challenges.

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We argue here that difficulties in LBML often become apparent in the learners' spatio-temporal behavior (i.e., their trajectory). A method and tool for the analysis of the learners' trajectories would help in identifying potential problems occurring during LBML, including those caused by decisions the teacher made during the design of the single learning units. Teachers could, for instance, apply spatio-temporal analyses on a learner's trajectory to identify problems, such as getting lost, running out of time, 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 for a better understanding of LBML mechanisms. Consequently, teachers could improve the tasks with respect to the learning goals, the spatio-temporal embedding, or the learning content, leading to improved learning outcomes for future LBML sessions.

The data necessary for this kind of analyses, such as trajectories measured using the Global Positioning System (GPS), can easily be collected with an LBML infrastructure. In general, the broad dissemination of mobile devices has resulted in large amounts of location tracking data, and corresponding analysis methods have been proposed in the Geographic Information Science (GIScience) literature (N. Andrienko, Andrienko, & Gatalsky, 2003). While most analysis methods for trajectories are designed to be performed fully-automated (Y. Zheng & Zhou, 2011), e.g., spatio-temporal data mining (Mamoulis, 2009), analysis methods based on visual analytics take the human analyst into account (semi-automated analysis) (G. Andrienko, Andrienko, & Wrobel, 2007). The underlying assumption of visual analytics is that by combining the strengths of machine (e.g., fast processing and visualization) and human (e.g., visual interpretation and domain knowledge), hypotheses on certain data patterns and on interpretations of these patterns may emerge.

This paper explores the opportunities of using visual analytics to analyze learners' trajectories for the evaluation of LBML concepts and platforms. We propose that LBML platforms should provide tools that support the visual analysis of one or several learners' trajectories.

We demonstrate the approach using several example trajectories recorded during different LBML sessions with the OMLETH platform (Sailer, Kiefer, & Raubal, 2015). The trajectories are visualized spatially as overlays on digital maps, as well as spatio-temporally in 3D visualizations. It is discussed how these visualizations may help to contribute to a better understanding of the dynamic process which took place during the learning session.

The following section reviews related work on the evaluation of Learning Management Systems (LMS) and LBML, as well as on trajectory analysis and visual analytics. We then introduce the study design with three different groups learning at two different locations. Using data collected during these learning sessions, it is then described how trajectory analyses can be utilized to evaluate LBML. The paper concludes with a discussion and an outlook on future work.

RELATED WORK

This section provides an overview of the literature on evaluating learning management systems (LMS) and LBML, as well as of methods for trajectory analysis of moving objects, including techniques for visual analytics of spatio-temporal data and map-based representation of space-time data in two and three dimensions.

Evaluation of Learning Management Systems

According to Szabo (2002), an LMS can be seen as a framework that unites and manages all aspects of the learning process. This framework yields several types of functions such as instructional content management, learning or training goal assessment, learning progress tracking and reporting of its data, as well as supervising the complete learning process. One important benefit of an LMS is the opportunity of providing lessons based on the individual student's learning progress (Szabo, 2002).

With the evolutionary growth of both, LMS and the tracking of students' performance, large data collections have become available. A similar evolution of growing datasets (often referred to as "big data") is known from other fields, such as social media, or payment systems and web tracking analytics (Siemens & Baker, 2012). A common characteristic of these data collections is the high level of detail. Thus, the goal of "big data" analysts is to detect patterns in these datasets to recommend allocations of resources, activities, or people (Duval, 2011).

Data analysis approaches involving the analyst (e.g., the teacher or learner) in the process, give her the advantage of familiarizing herself with the data and therefore being able to conduct a more meaningful analysis and interpretation (Duval, 2011). Thus, the analysis of data collected with LMS may help teachers make better choices that lead to improved learning outcomes (Szabo, 2002). Both, visualizations showing the activity of individual learners, and those visualizations for teacher-defined tasks, can help to evaluate the learning progress (Duval, 2011).

In contrast to conventional LMS described above, the systems supporting the management of LBML, for example, the OMLETH platform (Sailer, Kiefer, & Raubal, 2015), should additionally support the analysis and evaluation of environmental spatial and spatio-temporal data of the learners' movement, recorded by mobile devices. Such techniques can be used not only for assessing students—when, where and what functionality of the LMS they have used—but also for improving the teachers' production and reflection process in preparation of the following lesson.

Evaluation of Location-based Mobile Learning

Vavoula and Sharples (2009) proposed six challenges in evaluating mobile learning: 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.

Several researchers have reported on user evaluations of LBML, typically utilizing methods known from classical usability engineering, such as short questionnaires, semi-structured interviews on users' experiences (Naismith, Sharples, & Ting, 2005), or evaluations through each LBML peer group presenting their findings in front of the class, as well as through cross-team interviews and written short reports (Klopfer & Squire, 2008). While these evaluation methods typically provide data of high quality, they require a high effort for both learners and teachers, thus not scaling up to large groups of learners.

Some studies have specifically focused on the evaluation of the learners' spatial skills. Since students in LBML navigate in outdoor environments, these skills are highly relevant here, including the understanding of cartographic maps, orientation and wayfinding capabilities, or general spatial thinking. For instance, Bartoschek, Schwering, Li, and Münzer (2013) found in a study on a navigation game (Ori-Gami) that the interaction with the map was more intense for children who made more errors in orientation and wayfinding. Those errors, as well as the average distance and speed to find the right way, were determined by visually analysing GPS tracks. We argue here 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, a suggestion which has also been made in a workshop paper by the authors of this article (Sailer, Kiefer, Schito, & Raubal, 2015).

Trajectory Analysis of Moving Objects

Different methods for the analysis of physical activity and movement of objects, animals or humans have been developed. The structure of such movement tracks can be described by three components: space (where), time (when), and objects (what) (G. Andrienko et al., 2007; Peuquet & Duan, 1995). A combination of "when" and "where" describes the set of objects which are present at a given location at a given time. "When" and "what" together describe the location of a given object at a given time, and "where" and "what" determine the time that a given object occupied a given location (G. Andrienko, Andrienko, Bak, Keim, & Wrobel, 2013). Analysis tasks for spatio-temporal data are based on the types of changes occurring over time: existential changes, changes of spatial properties (location, shape) and thematic properties (attribute values) (G. Andrienko et al., 2013).

Methods for trajectory analysis have mainly been proposed in the geographic data mining community (Miller & Han, 2009), where these methods have been applied to a number of fields, such as wayfinding (Schmid, Richter, & Laube, 2009) and tourism research (Vu, Li, Law, & Ye, 2015; Y.-T. Zheng, Zha, & Chua, 2011).

G. Andrienko and Andrienko (2009) 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), simultaneous movements of multiple unrelated objects (e.g., the daily commuting behavior of all inhabitants of a city), and simultaneous 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 the literature fall into exactly one of these three categories. We will use this categorization later in this article.

For the movement of a single object, G. Andrienko, Andrienko, Burch, and Weiskopf (2012) 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 analyzing multiple unrelated objects, G. Andrienko and Andrienko (2009) suggest tasks about the use of space in general, for instance, the degree of accessibility or connection between objects. Other typical analysis tasks include the analysis of major flows or typical routes between places. Pattern analyses, such as concentration or dispersion, convergence or divergence, and propagation of movement characteristics are further types.

The analysis of relative movement of related objects investigates patterns, such as approaching, encountering, following, evading, etc. For related objects, the spatial proximity at a given time can be an indication for the interaction between these objects (G. Andrienko & Andrienko, 2009). For instance, the RElative MOtion (REMO) approach proposed by Laube, van Kreveld, and Imfeld (2005) 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. 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.

In the following, we consider spatio-temporal properties of both, single trajectories (i.e., one learner moving alone) and multiple trajectories (i.e., several learners moving either together as a group, or independent of each other in the same area).

Visual Analytics of Spatio-Temporal Data

The general aim of data analysis is to reveal unknown information. Exploratory approaches to data analysis are inductive. They start with an inspection of the data in order to get to know the phenomena and to develop a theory. By analyzing data visually, humans can benefit from the fact that their perception is primarily determined by the visual sense (Krygier, 1994). The primacy of sight allows for effective visual analysis and thus, enables the human capability of drawing conclusions by directly interacting with the data (Keim, 2002).

Research about the exploration of map-based spatio-temporal data dates back to the 1970s (Tobler, 1970). The author focused his studies on problems of urban growth and solved it with map-based animation techniques. Similar techniques to explore patterns of road traffic accidents were used in Moellering (1976). Meanwhile a number of studies have examined the use of dynamic visualization in spatio-temporal cartographic representation (G. Andrienko & Andrienko, 1999; N. Andrienko et al., 2003; Brunsdon, Corcoran, & Higgs, 2007; Koussoulakou & Kraak, 1992; Shepherd, 1995).

Large environmental datasets, such as human movement tracks, were seen as a major challenge in 1999 for geographic visualization, knowledge discovery in databases, as well as information sciences in general (MacEachren, Wachowicz, Edsall, Haug, & Masters, 1999). Based on a theoretical framework from the early 1990s, considerations were made about how representations of such knowledge discovery in databases can be used for the objectives of the visualization and the degree of interactivity (MacEachren et al., 1999). However, there was still a lack of methods for transforming the geospatial data into visually comprehensible information. This was later targeted by the research field of Geovisualization which utilizes methods from several fields, such as digital cartography, Geographic Information Systems (GIS), and Remote Sensing, including techniques, such as image analysis, information visualization, and exploratory data analysis (MacEachren & Kraak, 2001).

The term *visual analytics* was used for the first time in the report *Illuminate the path: The Research and Development Agenda for Visual Analytics* (Cook & Thomas, 2005). Based on the technique of visual data exploration, visual analytics is defined as visual data mining (G. Andrienko et al., 2013). As mentioned above in the section on the Evaluation of LMS, not only sensor data, social media big data or other large datasets can be analyzed by human-centered visual analytics or algorithm-centered data mining, but also data collected with LMS and other educational software. Another example is crime analysis, a field in which the map-based visualization of the spatial and temporal distribution of criminal incidents is a common method to detect crime patterns (Brunsdon et al., 2007).

Visual analytics tools provide solutions which enable analysts to focus their full perceptual and cognitive capabilities during their analytical work (G. Andrienko et al., 2007). Using these human capabilities, advanced computational capabilities have the task to augment their discovery process. In our context, we use several map-based techniques to enhance the analysis. We will use map-based representations in two as well as in three dimensions.

Previous research exploring space-time patterns in two dimensions (2D) has focused on the benefits of static maps as well as interactive dynamic visualization techniques (Brunsdon et al., 2007; Harrower & Fabrikant, 2008). Further techniques suitable for the visualization of changes include time labels or representation of the age, object or other attribute values by coloring. Further, querying (lookup and filtering) or map-based animation over time are often demanding techniques. Temporal animated maps, which are sometimes called movie maps, and the concepts which are known as "play-back" from video simulation, can help to understand the temporal evolution of the data. However, it has to be taken into account that maximal cognitive capacity of information per time-unit is limited (N. Andrienko et al., 2003; Harrower & Fabrikant, 2008).

The space-time cube representation is an information visualization technique in which spatio-temporal data records are mapped in three dimensions (3D) into a cube. These cube representations benefit users when analyzing complex spatio-temporal patterns (Kristensson et al., 2009). The benefit of using space-time cube representations is that temporal as well as spatial information are displayed simultaneously. This effect is difficult to achieve in other representations. A consequence and further advantage of this effect is that speed can also be explored simultaneously. In this representation, where time represents the vertical component, gently sloping path segments indicate fast movement, while steep segments correspond to slow motion. (G. Andrienko & Andrienko, 1999; N. Andrienko et al., 2003; Kristensson et al., 2009)

Class Planning and Follow-Up

Good teaching requires effective teaching methods (Borich, 2013; Dubs, 2009), however, to guarantee effectiveness, a solid class planning is necessary. In this respect, the class structure is an important key factor that further contains the announcement and monitoring of verifiable learning goals (Schneider & Stern, 2010). In addition, a class structure and tasks related to the students' real lives support them in building their own knowledge structure (Schneider & Stern, 2010). Thus, many teachers structure the learning content into several verifiable tasks that—individually or together—cover the learning goals defined.

A solid class planning requires teachers to reflect their teaching approach including the definition of learning goals intensively (Borich, 2013). This reflection process can be supported by actively switching between the student's and the teacher's perspective, whereas learning goals, tasks, and teaching methods are first reflected and then evaluated with regard to teaching and learning. Evaluating the effects first and then implementing the findings in the follow-up supports teachers to improve their teaching in the future (Angelo & Cross, 1993). Because every kind of teaching analysis fosters reflection, also visual analytics can contribute to an improvement of future learning tasks. Instead of relying on feedback or on abstract results of computational approaches, visual analytics of learner's trajectories can provide teachers with more accurate and unbiased information to evaluate a learning unit.

STUDY DESIGN

As described in the previous section, we structure our discussions in this article based on the classification of movement analysis tasks by G. Andrienko and Andrienko (2009): 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 studies were designed to collect data that is representative for all three categories.

This article presents first results of an ongoing exploratory research study. We decided to focus on three samples gathered at two different locations, which illustrate the different movement patterns addressing the research question. Participants were split into learning groups belonging to the same school class, while the classes were chosen by teachers interested in LBML. The dates of the study were chosen without consideration of environmental conditions. In the following, we will explain the different sites, procedures, participants, and evaluation techniques—including an explanation of data and software—before we continue with the map-based visual analytics and discussion.

Sites

Two very different sites were selected for the study: a rural site ("Jurapark Aargau", first run) and an urban site (Zurich, second and third run).

The rural site is located next to the village of Hottwil in the Jurapark Aargau, Switzerland. The single learning units were allocated on the hillside of the valley of Mettau. The site is rather agricultural and mostly covered with grass, providing a perfect overview over the valley. The opposite valley, the buildings of Hottwil, and the opposite mountain ridge represent typical landmarks supporting the wayfinding. The goal at this site was to find the seven learning units in a predefined order. The overall learning objective of this round-trip consisted of getting an overview of the park. The tasks varied between the single learning units and consisted of story-reading a text followed by peer-discussions, or comparing an image with the environment and describing the differences, or exploring elements of the physical environment and tagging them geo-spatially on an interactive map.

The urban city center of Zurich, Switzerland, delimited by the central business district and the old town, represented the second site of our studies. The area consists of many old buildings, cozy cafés, narrow alleys, and idyllic parks. Most of the streets are only open for public transport or pedestrians. The scope of the round-trip consisted of 13 single learning tasks which needed to be completed in a predefined order. The tasks in this case included story-reading, area exploration, analyzing, and discussing with the aim of perceiving and studying the historic as well as the current appearance of the city similar to "Jurapark Aargau".

Procedure, Participants, Material, Hardware and Software

Classes from three different high schools in the city of Zurich have participated in this ongoing study. One run was in Jurapark Aargau, the two other runs were in Zurich, where these two used the same learning module. Each run was conducted on different days. The LBML learning modules were integrated into the activities of a training camp on the one, and in those of regular school classes on the other hand. Participation was not graded. The participants were briefly introduced to

Table 1. Metadata of the three study runs

	Site	Participants / Tracked datasets	Group size	Distribution of tracking devices	Procedure	Conditions
First Run	Jurapark Aaragau	22 students between 15 and 18 years of age / 11 datasets	Group of two	One smartphone or tablet per group	Briefed to start separated and limited to 90 minutes	Early afternoon, approx. 20°C, dry
Second Run	City of Zurich	6 students between 18 and 21 years of age and two adults / 4 datasets	All together	One smartphone or tablet per participant	Group size at participants' choice, limited to 120 minutes	Late afternoon, approx. 33°C, dry
Third Run	City of Zurich	21 students between 15 and 17 years of age / 12 datasets	Random distribution, 9 single learners, 12 group learners in 4 groups	One smartphone or tablet per group or single learner	Briefed to start separated at predefined learning unit's location Limited to 60 minutes	Mid-morning, approx. 22°C, dry

the OMLETH interface and then either randomly assigned to a group of learners, or designated to proceed the study as a single learner. There was no intervention from the study supervisors when the composition of the learner groups changed during the run. Participants were able to meet others who were not necessarily part of their own group; these meetings and the resulting group behavior were one specific focus of this study. There was no pressure to fulfill all the learning units within maximum duration. Participants filled in an online survey of approximately 5 minutes directly after the run to reflect about their run (learning features, technology, and general impressions).

Participants were asked to use their own mobile devices for the run. They were advised to fully charge the smartphone batteries to guarantee operational reliability, and also to ensure the availability of 30 Mbytes for mobile data communication. Table 1 presents the specified properties per run, which are quite heterogeneous, as are the participant samples. This was intended due to the exploratory nature of the study.

To obtain the spatial footprint of movement tracks of all learners, or learner groups respectively, triples of location, user, and timestamp were recorded using the HTML5 Geolocation API with the streaming frequency parameter set per default to 0.5 Hz (one record per two seconds). An API-method was used to register a function that was called each time the position of the device changed. If the function is successful, it returns a coordinates object of the current location of the device. Sometimes this function takes several seconds. Because there is no built-in functionality in browser web apps for seamless position tracking, the corresponding application needs to be in use constantly to record the position continuously. Closing the application or changing the screen's status to sleeping mode stops the recording (Lubbers, Albers, & Salim, 2010). This factor resulted in time gaps as well as spatial gaps, as will be shown in the analysis sections.

Two software applications were used for the analysis of the spatio-temporal trajectories:

First, we used V-Analytics[1] to bundle a number of approaches, techniques, and methods to create visual analytics visualizations for spatial and temporal data (Sakr et al., 2011). This includes, for instance, the space-time cube technique for visualizing the movement tracks in three dimensions with the time plotted on the z-axis (Sakr et al., 2011). Then, we used the commercial GIS ArcGIS (by Esri[2]) to combine different kinds of geo web services[3] (such as, satellite imagery, street information, or maps from OpenStreetMap), facilitating the analysis of the trajectories with respect to the geographical context (Tang & Selwood, 2003).

The next section describes how we used these applications for map-based visual analytics of spatio-temporal data in LBML.

VISUAL ANALYTICS OF LEARNERS' MOVEMENT

The goal of the visual analytics analyses was to find interesting LBML-related events in the spatio-temporal trajectories by visualizing them in a map-based context. We structure this section based on the three movement analysis types (G. Andrienko & Andrienko, 2009). For each section, we start with 2D-map-based visual analytics and continue with the 3D-map-based technique based on space-time cubes.

Analytics of Single Learners' Movement

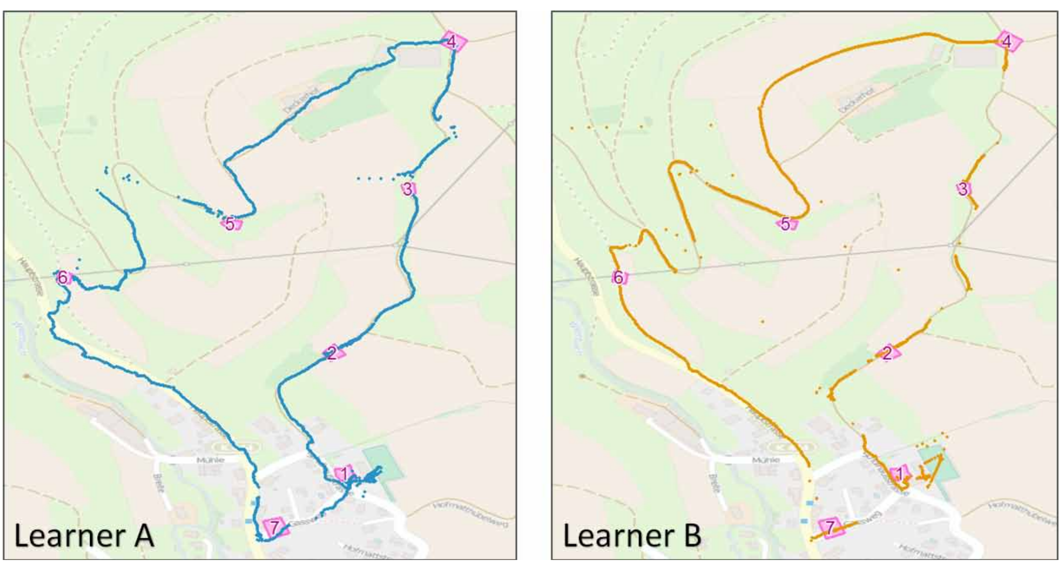
A feasible method for analyzing learners' movement data is by visualizing the data on a 2D map. A quick look on the map reveals whether the students fulfilled the teacher's demand or expectations of following the optimal path. Irregularities indicate that something must have happened that needs a more profound analysis. However, finding the reason for an irregularity is not always evident (e.g., incorrect location of the learning unit, incorrect unit order, etc.).

Paths can be visualized as collections of point representations (point cloud; see Figure 1) or as trajectories (sequence of point representations; see Figure 4). When visualizing only the point cloud, the sequence cannot be interpreted with certainty. Further analysis or interactive techniques are required.

A static 2D cartographic representation requires a map to facilitate orientation and to provide context information to understand the learning unit representations (polygons) as well as the learner's recorded trajectory. In Figure 1, the trajectories of two single learners are displayed as two single-colored point clouds on two static 2D maps. The visualization shows obvious facts: every spot containing a learning unit had been visited and learner A followed mostly the path intended by the teacher. Only between learning units 5 and 7, some uncertainties still remain.

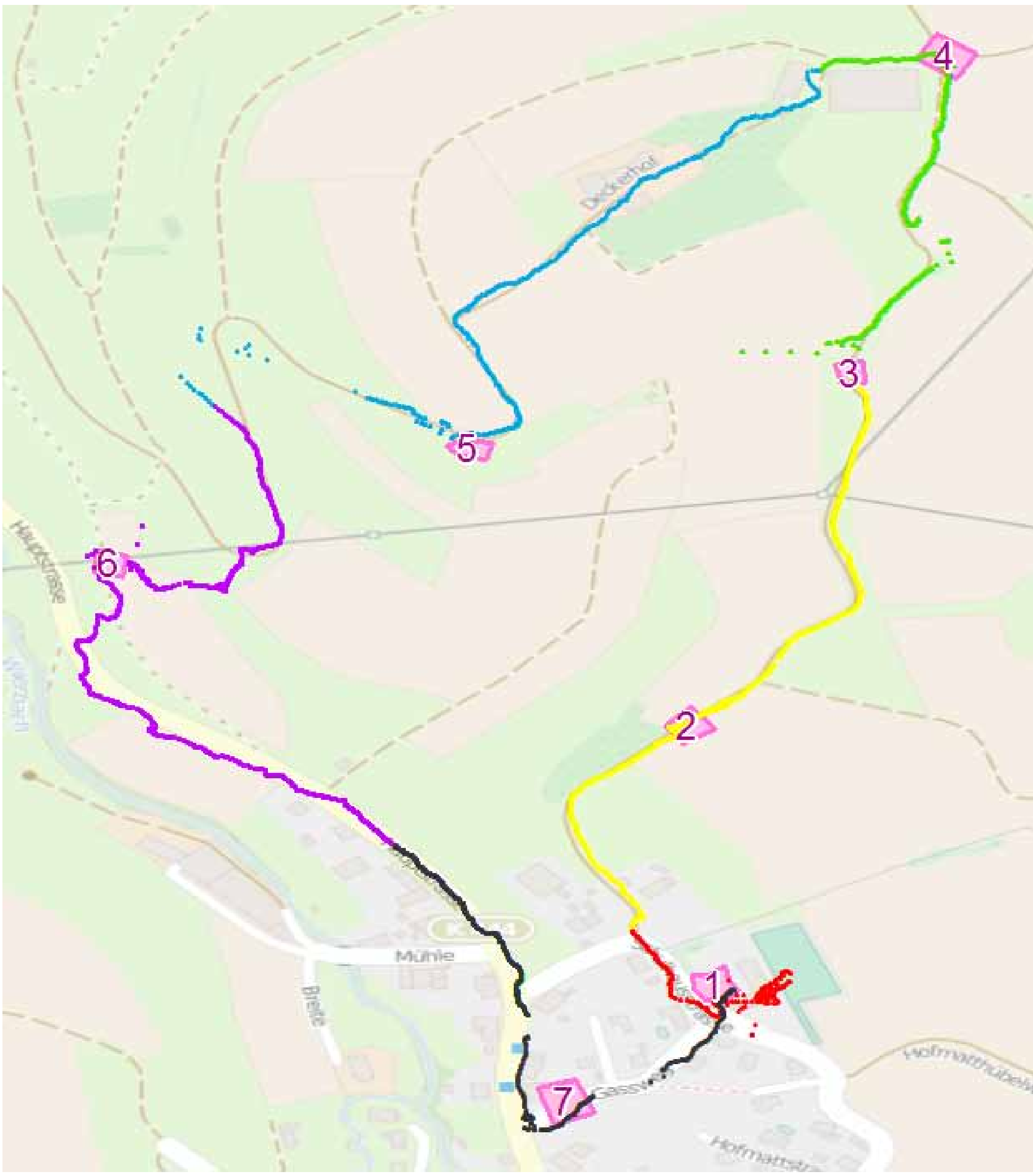
The static 2D map cannot provide information about start and end point, the time the learner spent at the learning unit, and in which direction she walked. Later, queries revealed that the single learner

Figure 1. 1st Study, "Jurapark Aargau": The trajectories of two single learners executing a field trip are visualized as two single-colored point clouds on 2D maps. The learning units are numbered and marked with pink polygons. Both, single learner A (blue) and single learner B (brown) visited every learning unit, however, in this static 2D map representation it is not possible to determine at which learning unit the field trip started or whether the learning units were visited in ascending or descending order (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)



started at learning unit 1 and proceeded counterclockwise ending again at learning unit 1. But, incremental querying can be very time-consuming. Therefore, coloring the path based on time can be very efficient to retrieve information about the temporal course visually. Figure 2 shows a "color ramp" symbolization based on the timestamp attribute where all GPS points recorded during the first 10 minutes are colored red. Each additional 10 minutes are represented in another color. What is missing in this representation is clear evidence about the learner's walking speed and the time consumption spent at the different learning units. Nevertheless, it can be derived based on the steadily recorded points—which indicate a

Figure 2. 1st Study, "Jurapark Aargau": The trajectory of single learner A (see Figure 1) executing a field trip is visualized as a point cloud on a 2D map. The time elapsed is shown by different colors in intervals of 10 minutes. Although the representation may not provide clear evidence about the walking speed and the exact time the single learner spent at the different learning units, the point distribution indicates that the learner walked steadily and solved the tasks quickly (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)



steady speed—that the single learner spent less than 10 minutes at learning unit 2. Thus, teachers can assert that the single learner solved the task at learning unit 2 quickly.

For a quick overview, 2D-map-based analyses as described, are sufficient, however they cannot provide a comprehensive description of the learner's activities.

Temporal animation yields an alternative way of visualizing the trajectory in 2D, an interactive technique which visualizes changes over time by moving symbols. Animations are, for instance, provided by GIS and are configurable regarding start and end time, the analyzed time interval, and the speed. Compared to the static map, this function can be advantageous because temporal information becomes visible more intuitively. However, a good animation configuration can also be challenging (Harrower & Fabrikant, 2008).

With the described techniques (coloring, animation), we have gained first insights on the learner's activity. The next section focuses on specific questions about wayfinding issues, speed recognition, and missing data in a single learner's trajectory as well as relatedness and unrelatedness of multiple learners' trajectories.

Wayfinding

Wayfinding is a behavior that describes a purposeful, directed and motivated movement from an origin to a specific distant destination in large-scale spaces such as landscapes, cities, and buildings (Golledge, 1999). People need various spatial and cognitive abilities to find their way. LBML typically requires learners to explore and plan a route at their own choice and responsibility. Research in the field of spatial cognition has shown that people use landmarks (known also as Points Of Interests (POI)) during spatial reasoning and communication of routes, therefore such landmarks can also be relevant for this study (Raubal & Winter, 2002).

Figure 1 shows that the trajectories between learning unit 1 and 3 of learners A and B fit well to the path represented in the map. The map demonstrates that there were not many other paths available, that the existing path would probably turn into the obvious route in relation to the decision makers (learners). The resulting movement tracks support this hypothesis. Therefore, it seems that wayfinding was not very challenging in the beginning of this field trip.

Comparing learner A's with learner B's track (Figure 1), a difference in the chosen route can be observed after learning unit 4. Learner A took the left and short path to learning unit 5, while learner B took the path to the right at the junction leading to a detour. There could be several reasons for these different route choices, such as differences in spatial abilities or subjective preferences (e.g., w.r.t. slope) for one of the route options in the decision situation (Giannopoulos, Kiefer, Raubal, Richter, & Thrash, 2014). If the route choice matters in relation to the learning experience, the teacher could for instance add further learning units as landmarks.

Choosing a constructivist and learner-centered approach of free exploration and self-navigation, the OMLETH platform does not offer an option to propose and sketch a predefined route for teachers. Instead, teachers plan the distribution of the learning units together with a mentally planned virtual path which they hope students are going to follow. Students navigate between learning units with a visualization showing a basemap and polygons, which means that they use the street network, cardinal directions, and/or landmarks included in the basemap for navigation. During the teacher's evaluation the spatial analysis can reveal deviations of the chosen path from the path the teacher had in mind, such as detours or false directions. These observations and analyses are of significance for teachers to learn from their learners' walking behavior for future learning module designs. Besides the improvement of the lessons, the analysis of a single learner's track also enables the teacher to provide help to specific learners.

A particular observation in human movement tracks is the existence of zig-zag paths. A zig-zag path means that the trajectory of a single learner shows a movement sequence of frequent direction changes. This kind of behavior is more often observed for children who make more errors in orientation and wayfinding due to difficulties in connecting the real-world environment to its spatial representation on a base map (Bartoschek et al., 2013).

Again comparing learner A with learner B during learning unit 6 (Figure 1), we see that learner A took a “zig-zag“-like path directly to the main road underneath, while learner B took a narrow path parallel to the main road. The analytics of such a “zig-zag” path segment could be an indicator for orientation problems or uncertainty, meaning that the first learner had problems in map reading or wayfinding. Probably the learner made purposeful “zig-zag” movements to tackle the elevation difference when walking down towards the road. These assumptions show that it is difficult to draw a final conclusion in this example.

Figure 3 shows a single learner’s track during the second study in Zurich. Following this single learner from the start at learning unit 1 on the way to learning unit 2, an unexpected distribution of

Figure 3. 2nd Study, “Legends of Zurich”: Single learner executing a field trip. The points tracked are represented as a unicolored point cloud on a 2D map whereas the learning units are numbered and marked with pink polygons (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)

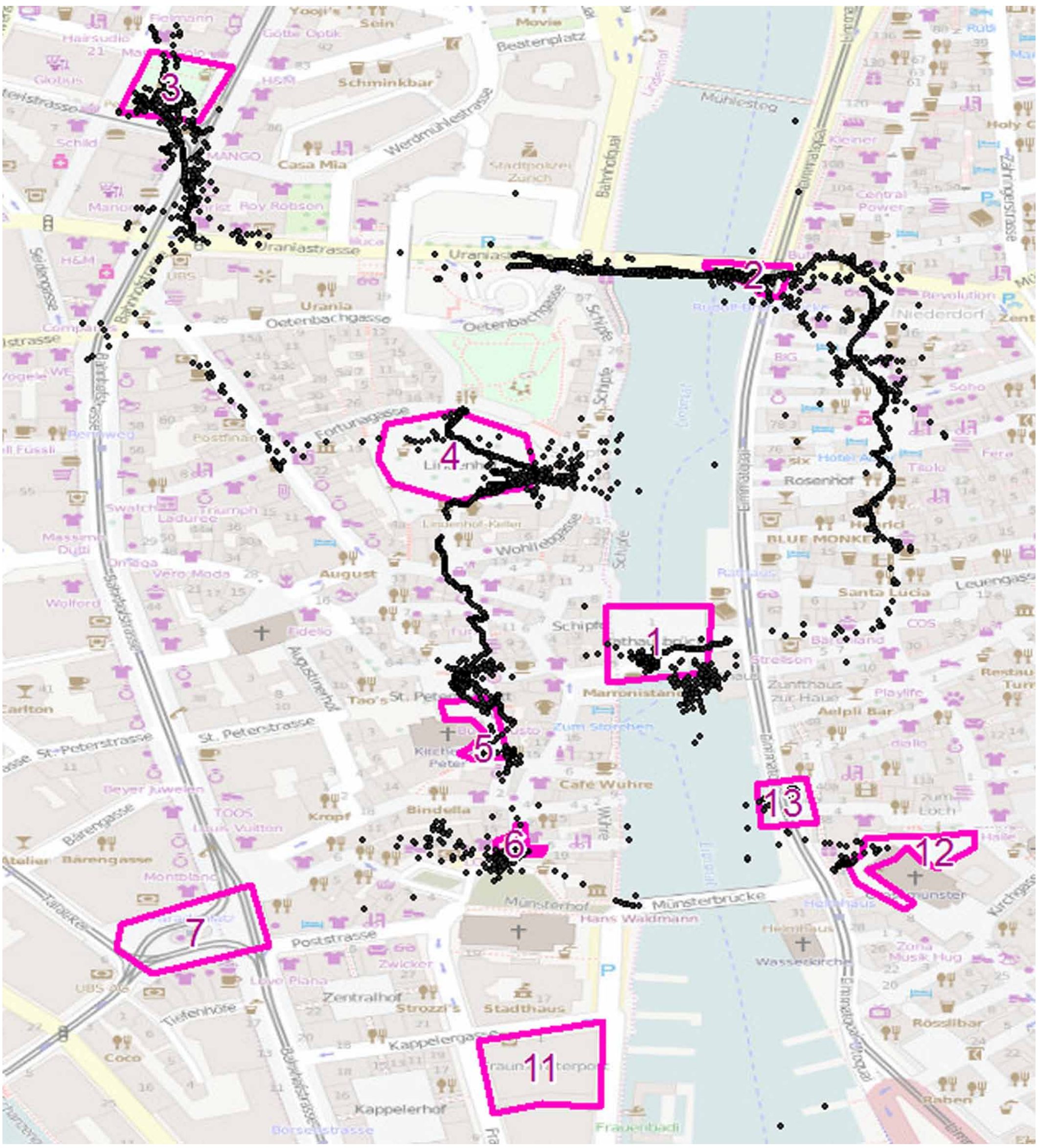
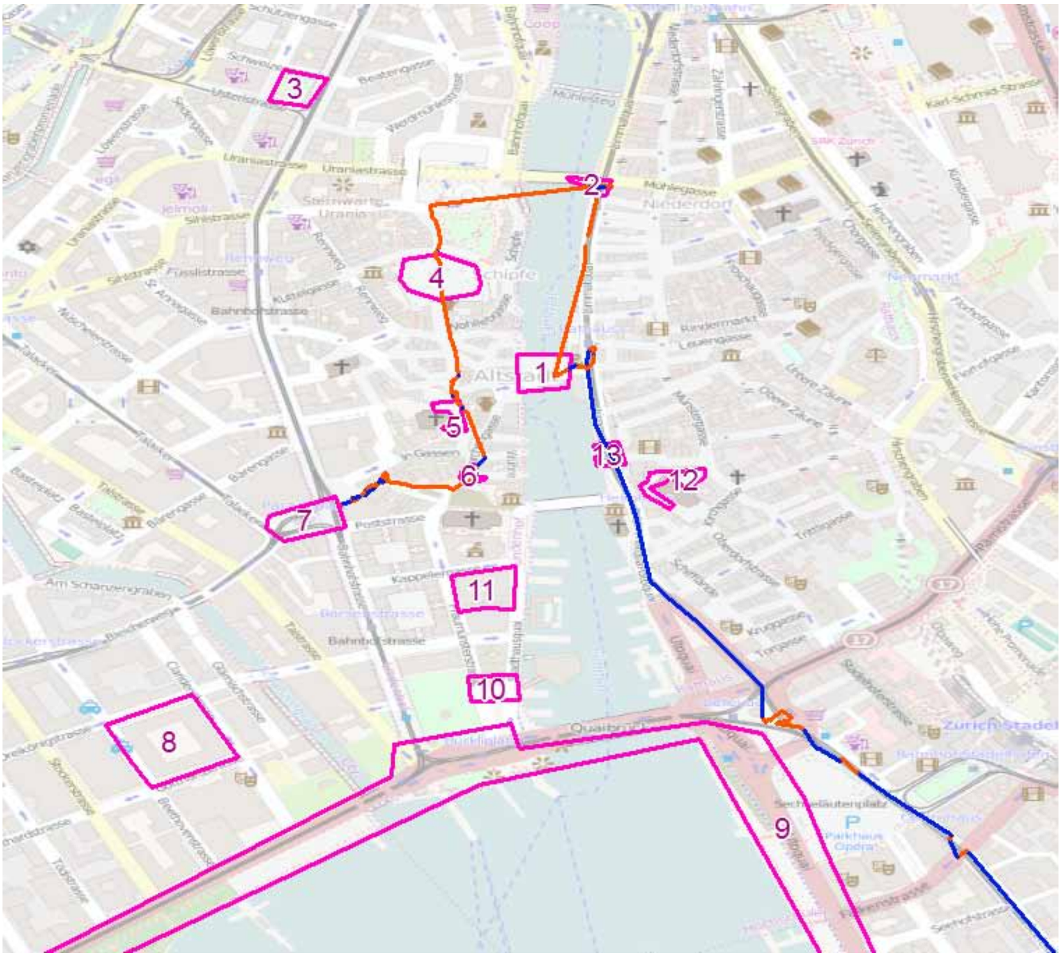


Figure 4. 3rd Study, "Legends of Zurich": The path of a single learner is represented as a continuous trajectory and shows her speed. The trajectory is colored in two categories where blue segments indicate the use of public transport (fast) and orange segments indicate walking (slow). The learning units are numbered and marked with pink polygons. (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)



data records can be identified. Instead of along the river, the records can be seen inside the eastern building area. The reason for this effect could be determined by the post-interview: due to the tropical heat that afternoon, the learner searched for a cooler route in the shadow of the narrow road. However, this detour caused a short time delay behind the predicted arrival time at learning unit 2.

Another unexpected event can be detected at learning unit 4 (see Figure 3) where students had the task of exploring the surrounding inside the virtual border of the learning units: the learner stayed at that place longer than expected and mostly at the border or next to the learning unit area. The learner's feedback in the interview revealed that the time duration was caused not due to profound task exploring, but due to the presence of a famous song writer taking a video recording of her song. Consequently, solving the task seriously was very challenging due to the distraction by the singer. Finally, the learner could not finish the whole learning module in the given time and had to shorten the way by proceeding from learning unit 6 directly to learning units 12 and 13.

What can a teacher conclude from this? Good planning is essential. Environmental factors and time matter. The teacher should carefully consider on which factors could influence and disturb the single learning units (Sailer, Schito, et al., 2015). The disruptive effects of this run (informal learning environments by Tan, Liu, and Burkle (2013)) might motivate and engage the learners to gladly execute these units again. Therefore, space for repetition to accomplish the tasks and achieve the learning goals should be provided. Finally, a follow up is also essential with a summary and a reflection phase (debriefing) after the outdoor learning module.

Speed

Speed is a property of the movement data. The rate of the motion, change, or activity is calculated by the distance of time intervals or the duration of distance intervals (Buchin, Driemel, van Kreveld, & Sacristán, 2010).

Figure 4 shows an individual learner's speed trajectory recorded during the third study (Zurich). The orange color indicates a speed between 0 and 2 meters per second (walking speed), the blue color a speed between 2 and 10 meters per second. The learner started the trip at the bottom-right corner, moved towards learning unit 1, and accomplished the module until unit 7. The evaluation of this speed trajectory shows two stages: first, a very fast movement towards unit 1 by displaying mostly blue segments with short orange (slow) interruptions, and second orange segments indicating slow walking speed. The characteristics of the first stage are typical for public transport systems, such as trams. With the map-based context, single stations and tracks of the tram line can be identified along the learner's route. Afterwards, the learner has moved from learning unit 1 to units 2, 4, 5, 6, and 7 very continuously at the rate of walking speed.

To sum up, the trajectory suggests that the learner initially took the tram to get to the start of the module and then reached all the learning units by walking. The post interviews verified this assumption.

No Data

One characteristic of motion tracks is that they consist of data recorded at distinct times (rather than continuous trajectories). There are moments in time for which no data are available (G. Andrienko et al., 2013), either due to the recording frequency of the device and app configuration (such as, 0.5 Hz), or due to limitations of the positioning technology (such as, limited GPS availability).

For instance, this observation is made for learner A in Figure 1, where at the curve of the small road after learning unit 5 towards learning unit 6, a gap of no data has appeared, although the learner must have passed this section.

In our case, in post-study interviews the app configuration could be identified as the main reason: as described above, (see Procedure, Subjects and Material), the app did not record data when the device was switched to sleeping mode or when the app was switched to the background. Possible reasons for this app usage behavior include: the learner was sure of his wayfinding abilities and preferred walking without using the smartphone; the learner switched to another application for an unknown reason; or third, the learner was worried about the battery life of the mobile device.

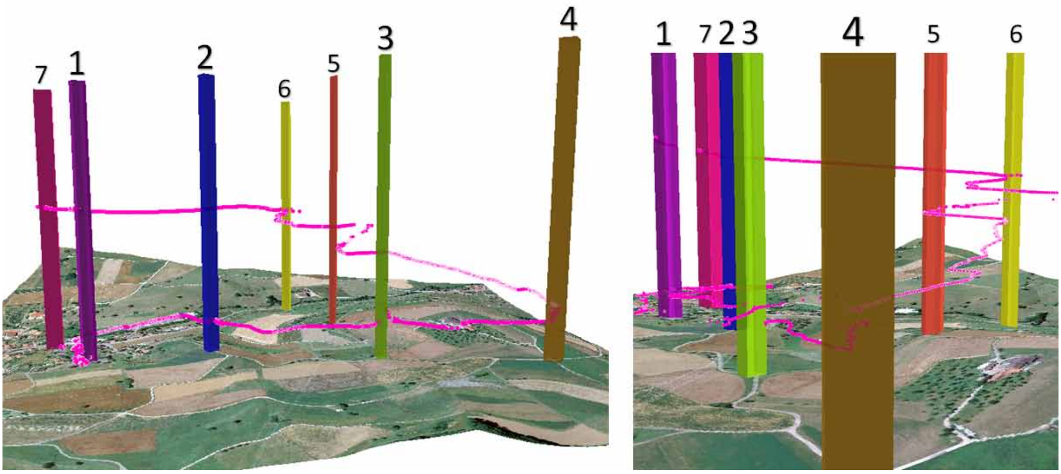
Movement and Speed in the Space-Time Cube

The visualization in 3D has the main advantage that it enables us to represent not only space, but also time. Refer, for instance, to Figure 5 for an example: the space-time cube is a perspective view of a three-dimensional representation over an underlying map where two horizontal dimensions represent the spatial extent, and the vertical dimension visualizes the course of time. The temporal axis is oriented from the bottom to the top, starting from the first space-time position (G. Andrienko et al., 2013).

Figure 5 shows similar findings as described above for the 2D representation, such as counterclockwise movement, no long stops or breaks, and confirmed the constant use of the app through the seamless record collection with the same walking speed.

This speed can be detected as the slope of the movement track in the space-time cube. The steeper the track, the slower the speed of the walking object. A vertical line segment indicates a stable and remaining position of the object. Such vertical segments can be detected in Figure 5, for instance

Figure 5. 1st Study, "Jurapark Aargau": The trajectory of a single learner's field trip (left: full extent, right: zoomed extent inside learning unit 4) is visualized in a space-time cube. Delimited areas containing learning units are numbered and extruded to 3D (software: © ArcScene 9.3, Esri; basemap: © swisstopo)



inside learning unit 4 (the space-time stations, refer to Miller (2005)). Shorter and longer occupation in these learning units can be analyzed through this visualization technique.

To explore single parts of the trajectory in more detail, several interaction techniques are proposed: a temporal focusing by expanding the vertical time component, a moving or zooming of the cube, to search for more precise effects, and a rotating of the cube to the view from another geographic direction (G. Andrienko et al., 2013).

Analytics of Multiple Learners' Movement

Analyzing the tracks of multiple learners can reveal further information useful for the teacher. Multiple learners can be either unrelated or related to each other, which is likely to effect the individual behavior, cause different movement patterns, and thus, requires particular analysis foci.

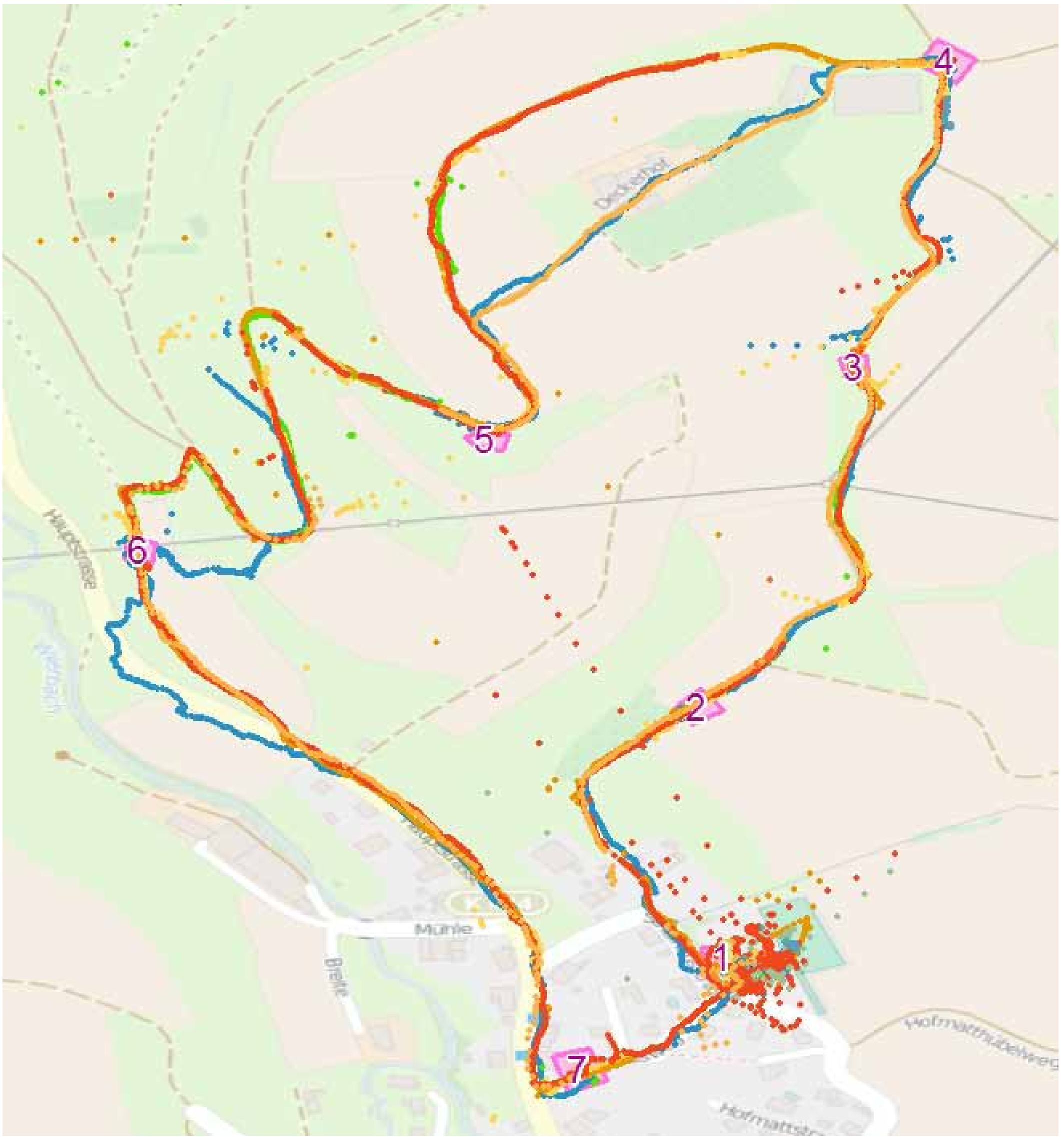
Movement of Multiple Unrelated Learners

LBML happens unrelated if learners are spatially, temporally, or spatio-temporally separated from each other and do not communicate or work together (e.g., through a chat) which would influence their individual learning process. It is difficult for teachers to ascertain that LBML took place unrelatedly, especially when working with visual analysis. For instance, what is the minimum spatial distance required? Obviously, ensuring unrelatedness in LBML requires teachers to be conscious about the class planning and the LBML unit conduct.

Besides the planning, also the movement analysis of multiple unrelated learners is challenging. Large datasets of tracked points can support the identification of users who showed similar movement, e.g., Yuan and Raubal (2014) and, based on these similarities, detect clusters of similar behavior. Nevertheless, although providing advice to solve the tasks independently, humans tend to organize in groups for social reasons and to profit from their peers' effort. In this case, however, the decisions taken are influenced by others. Thus, it must be analyzed first, if a possible relatedness could be detected.

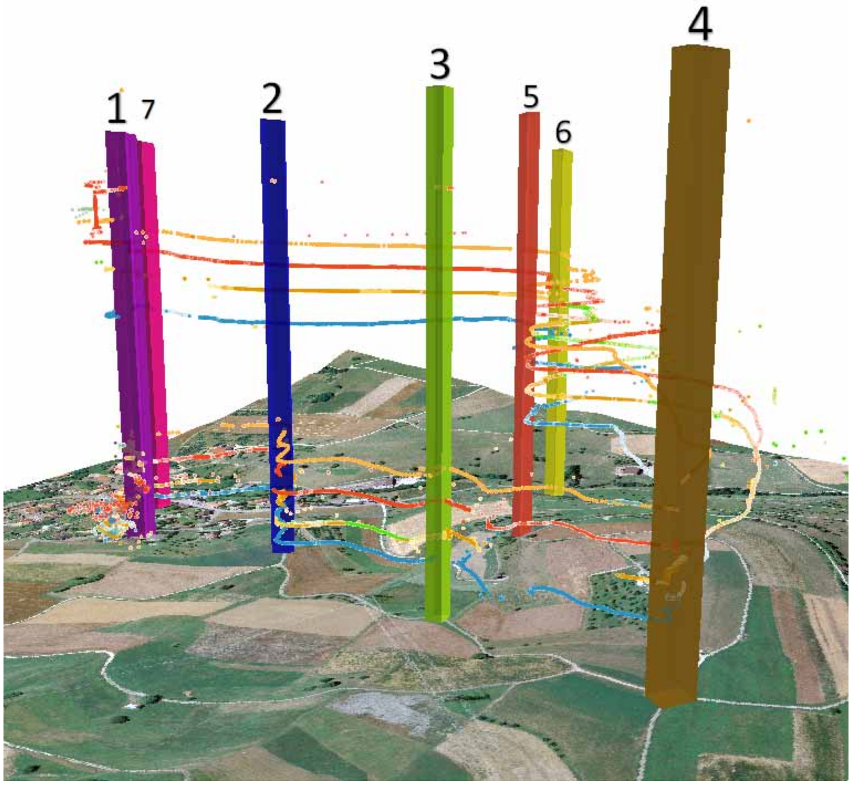
Maps offer limited options for detecting temporal relatedness. Both Figure 6 and Figure 7 show the tracks of the run in "Jurapark Aargau". In interactive 2D maps, single paths can be blended in and out and often allow retrieval of additional information stored in the underlying geodatabase. Thus, interactivity might provide possibilities to enable the analysis of all aggregated trajectory properties

Figure 6. 1st Study, "Jurapark Aargau": 11 learners decided to proceed on the field trip on different routes. All tracks are differentiated by colors and visualized as point clouds on a static 2D map. Note the dotted straight lines that show evidence of positioning problems (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)



for each user. To simplify the visual analysis, individual learners or groups are distinguished using different colors. Areas with a high point density could be identified, e.g., through spatial clustering (G. Andrienko et al., 2012) as points of interest (POI) or as a popular route. Single points or path segments can be further colored using a gradient that represents the time course. However, distinguishing different levels of brightness or hue (e.g., Figure 2) might be challenging for data analysis when it comes to multiple trajectories. Instead, animated paths displaying each user's position depending on the time course could be a feasible approach. Moreover, it can easily be revealed if two learners stood close together at the same time. Compared with static maps, interactive tools offer various options to support visual analysis.

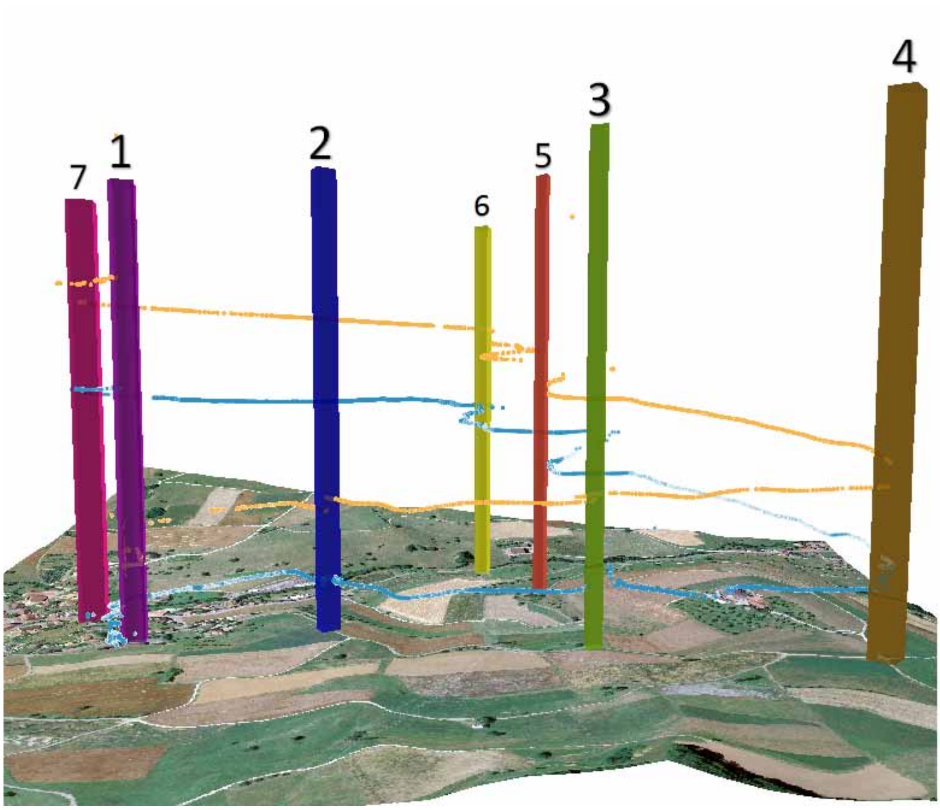
Figure 7. 1st Study, "Jurapark Aargau": 11 learners executing a field trip are differentiated by color and visualized in a space-time cube. Delimited areas containing learning units are numbered and extruded to 3D (software: © ArcScene 10.3, Esri; basemap: © swisstopo)



In general, Figure 6 shows that the students primarily chose similar paths to complete the field trip. The blue learner deviated most from the optimal path. Furthermore, one fork could be found in the upper part of Figure 6 where the learners almost evenly decided to proceed to the left or to the right. In addition, the almost regularly dotted straight lines could be determined as GPS measurement errors that occur during the process of searching for GPS satellites. Assuming that most GPS measurement errors occur while the devices are turned on and most time is spent during briefing and debriefing, the start and end point could be located within the area of the highest visual dot density in the mid-right bottom of learning unit 1.

In contrast, the representation shown in Figure 7 is more versatile compared to the 2D map of Figure 6 because the evaluator can change the camera settings interactively, thus switching between 2D and 3D visualization. Furthermore, the tracks of Figure 7 are visualized as a space-time cube. Parallel trajectories show that the learners were at the same positions but not at the same time. Similar differences indicate that learners were on the way at a more or less similar speed, but conclude the spatial unrelatedness to each other at this movement segment. In contrast, tangent or intersecting lines show that learners had the opportunity to meet each other because they were at the same place at the same time. A shallow slope indicates high movement velocity and vice versa. Vertical lines indicate that the learner spent time at the same place (N. Andrienko et al., 2003). The parallel paths of the interactive space-time cube of Figure 8 reveal that the learners walked with a similar velocity and that the learners were unrelated to each other.

Figure 8. 1st Study, "Jurapark Aargau": Learner A (blue) and Learner B (orange) (see Figure 1) executing a field trip are visualized in a space-time cube. Delimited areas containing learning units are numbered and extruded to 3D (software: © ArcScene 10.3, Esri; basemap: © swisstopo)



Analyzing a space-time cube reveals also facts concerning temporal issues. In Figure 8, two tracks of the field trip in "Jurapark Aargau" were isolated to make only two learners (blue and orange) visible. Visual analysis reveals that the vertical distance between both paths increases over time, however, most remarkably at learning unit 4 (brown learning unit on the right margin of Figure 8). Thus, the orange learner, who started later, spent more time at learning unit 4 compared to the blue learner.

Movements of Multiple Related Learners

Learning can also occur within a group that pursues the same target. When competences as an arrangement of knowledge, skills and attitudes, are applied within a group of learners, several aspects can influence learning, such as motivational, social, and cognitive aspects. Motivation can have a positive impact on cognition and social aspects such as group cohesion within peers (Wentzel, 1998). Improvements in cognitive learning can lead to increased self-confidence which may stimulate again the motivation and social skills (responsibility). The whole arrangement of the motivational, social, and cognitive dimensions and its interrelations for group-based learning could support the distribution of cognition across and between individuals (Hattie, 2013; Salomon, 1993; Strijbos, 2004).

Consequently, we believe that the resulting movement patterns of multiple physically related learners may indicate motivational, cognitive, and social aspects within a group. The trendsetter motion pattern, for instance, was introduced by Laube et al. (2005) 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. Other types of followers, however, prefer to evade the responsibility of contributing to the group's success. One possible assumption here is that interested learners are located close to the leader, moving at the same speed along the route, while less interested followers are located more distant to the group leader. If these assumptions hold, the speed pattern may provide evidence for distinguishing between interested and uninterested learners.

Both Figure 9 and Figure 10 (full extent) show the tracks of the second run—once as a point cloud on a 2D map and once as a space-time cube. The learners were advised to start at learning unit 1 and progress increasingly to learning unit 13. By their own choice, the group remained spatially

Figure 9. 2nd Study, "Legends of Zurich": The tracks of 4 learners are differentiated by colors and visualized as point clouds on a 2D map. The learning units are numbered and marked with pink polygons. Note that the learning units 7 and 11 have not been visited (software: © ArcGIS for Desktop 10.3, Esri; basemap: © OpenStreetMap)

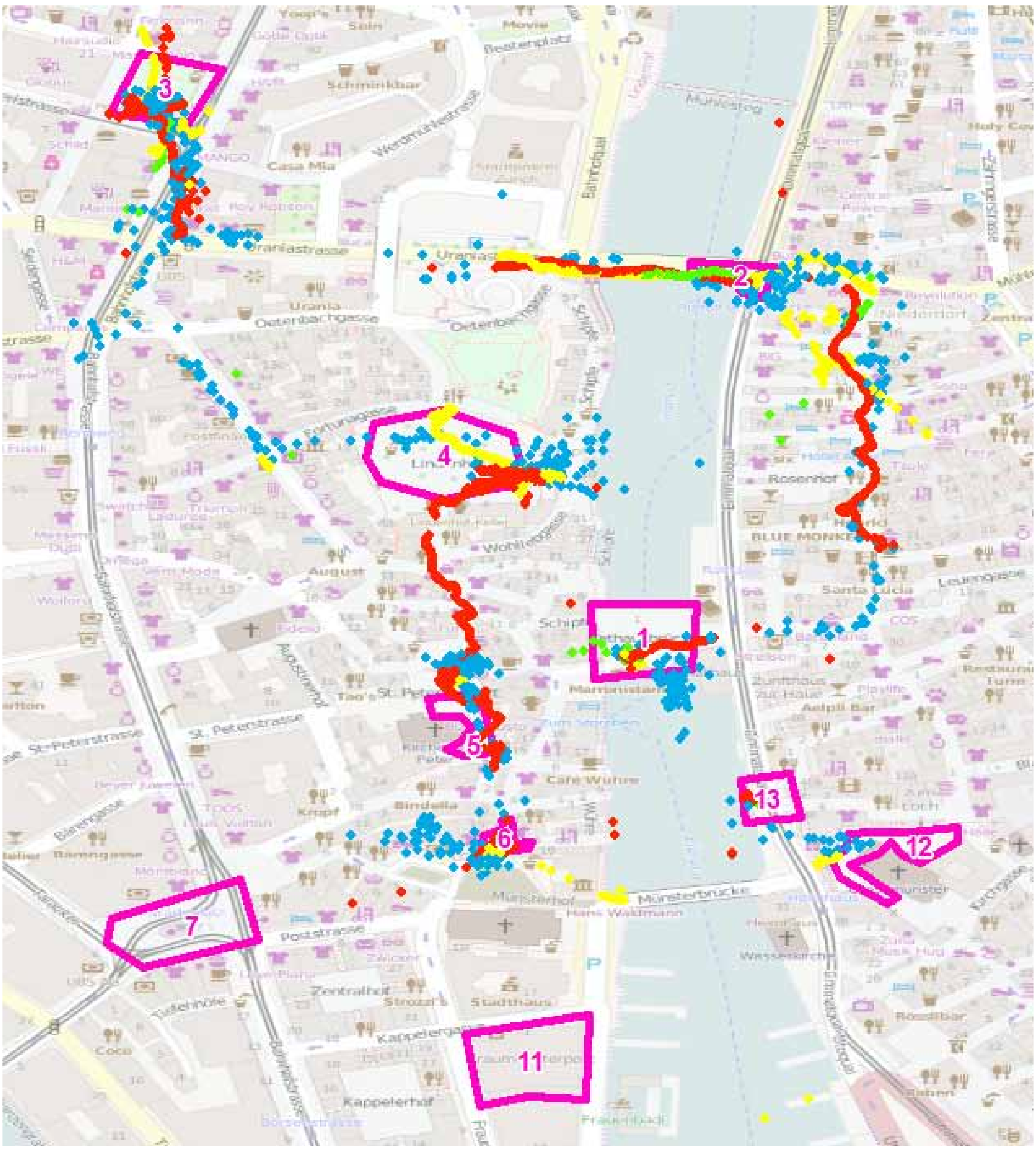
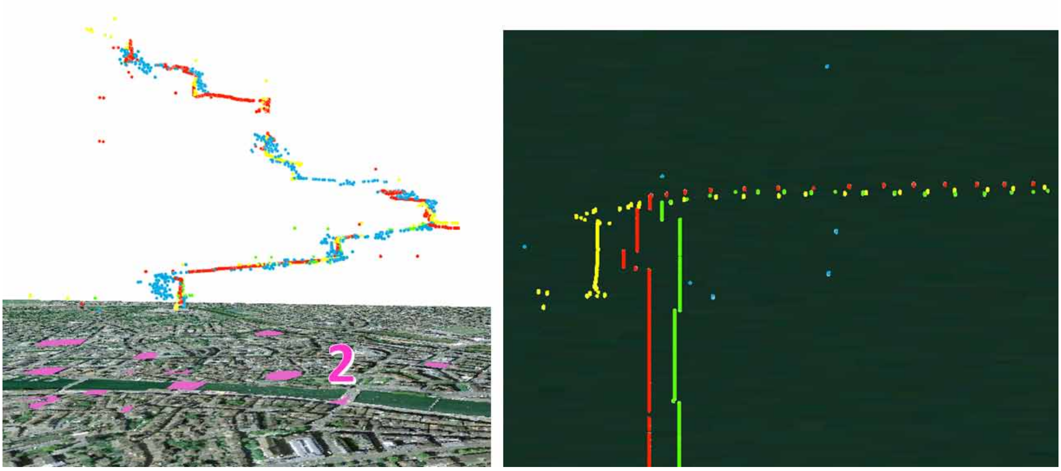


Figure 10. 2nd Study, "Legends of Zurich": 4 tracks of learners executing a field trip (left: full extent, right: zoomed extent to learning unit 2) are differentiated by color and visualized in a space-time cube. One tracked adult is represented by a yellow track. Delimited areas containing a learning unit are marked with pink polygons, whereas the learning unit 2 is highlighted by labeling (left). A closer look at the learning unit 2 (right) shows that the adult often leads the group (software: © ArcScene 10.3, Esri; basemap: © swisstopo)



close during the whole procedure. The visual analysis of Figure 9 shows a path-like pattern with accumulated points at the different spots. The detour between learning unit 1 and 2 already observed for a single learner in Figure 3 can also be detected of the whole group. The reason is known, but who was the decision-maker (trend-setter) within this group? Unfortunately, due to missing records, we cannot approach this question closer.

The visual analysis of the space-time cube shown in Figure 10 demonstrates that all learners moved as a group. However, there are notable gaps in each track. For instance, the green learner was not tracked after one third of the time had elapsed.

It could be interesting for the analyst to detect the trendsetter who influenced the other learners concerning locomotion, navigation, decision-making about stops, speed, or directions. However, unilateral leadership (in Figure 10; adult = yellow) could be obstructive to the balanced support and character building of other learners. By zooming close to the single trajectories, for instance at learning unit 2 (Figure 10 zoomed extend to the learning unit 2), the yellow learner made the breakaway first and is often two to four seconds earlier than the rest of the group, thus, he would hinder other learners to consolidate leadership skills. Thus, these findings could help teachers to create tasks that address diverse learner characteristics. Tracking gaps, however, do not allow to derive a statement about the universal leading role of the yellow learner.

Beside the trendsetter motion pattern, Laube et al. (2005) described two other patterns. We could not detect the concurrence motion pattern with its crossing trajectories in our data. For teachers, this motion pattern would also be helpful to improve the tasks given to avoid concurrence and thus to foster cooperative learning. However, we found the constant motion pattern with its non-cutting trajectories in all three runs during locomotion from one to another spot. Teachers might be interested in knowing who acts as quiet follower in order to foster this specific learner by adapting the tasks or by giving her the advice to take the leading role.

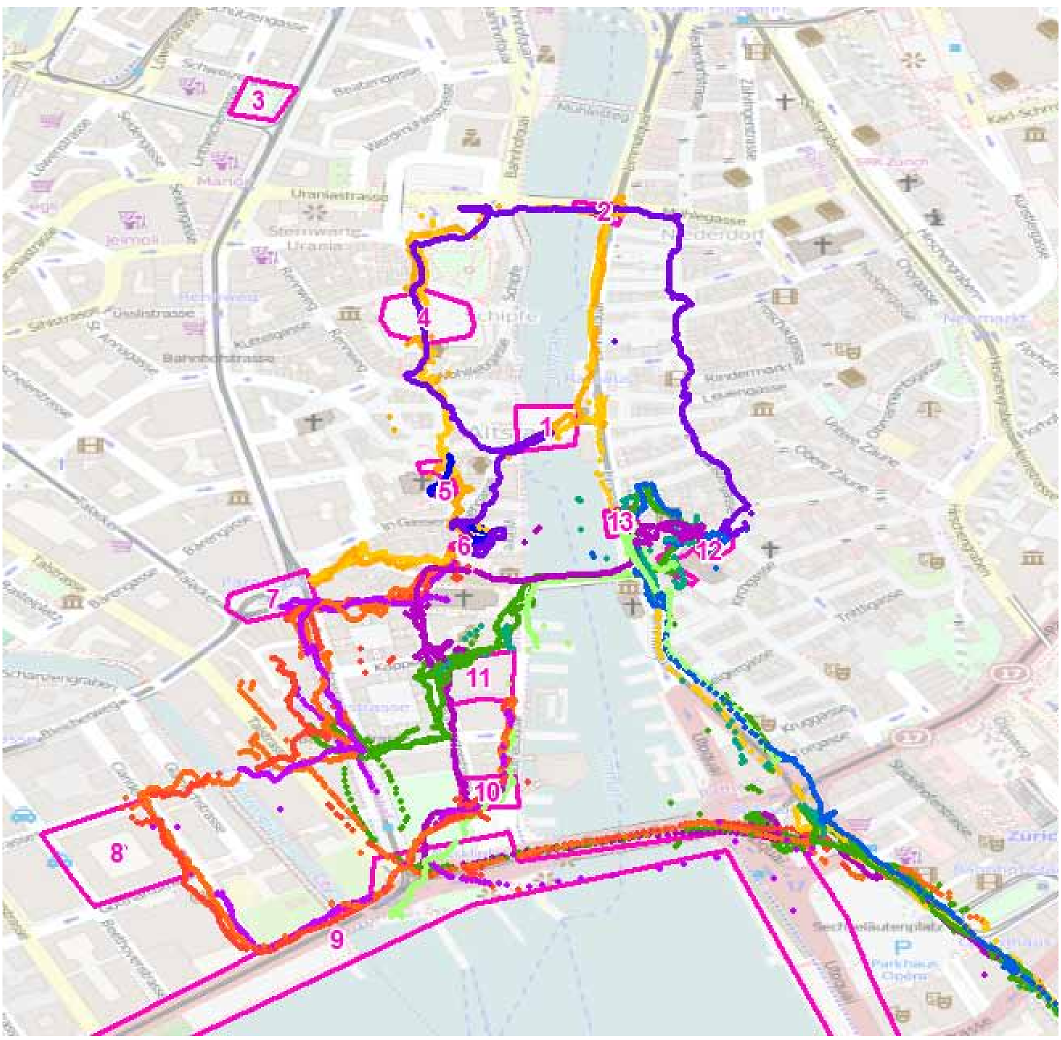
Finally, every kind of learning module evaluation contributes to recognizing good and weak points in the learning module. These findings are relevant for improving the subsequent learning module. Thus, learning module evaluation is crucial to keep or raise the teaching quality.

Revelation of Misdirection or Cheating

Another type of pattern we specifically found in our data is related to misdirection or cheating. In order to improve LBML units, evaluators are interested in the reasons that led to misdirection. Such reasons could comprise errors in the task description, task misunderstanding, technical failure, and even cheating. Of course, distinguishing between deliberate and unintentional actions based on visual data analysis is a balancing act. Neither, mischief should be presumed per se.

Figure 11 shows no data records towards and away from learning unit 3 of single learners and group-based learners. It seems that all learners skipped this unit 3 even though it should have been followed consecutively after unit 2. The analysis revealed that after completing the task at unit 2, learners were misdirected by a wrong configuration of the app which led them to unit 4 instead. Thus, the tracks did not correspond to the evaluator's expectation due to a conceptual error (type error) in the design of learning unit 2.

Figure 11. 3rd Study, "Legends of Zurich": The tracks of 12 single learners and groups are differentiated by colors and visualized as point clouds on a 2D map. The learning units are numbered and marked with pink polygons. The distinction between the colors highlights the spatial clustering, however, it is not possible to provide evidence about the exact path walked over time (software: © ArcGIS for Desktop 10.3, Esri; basemap:© OpenStreetMap)



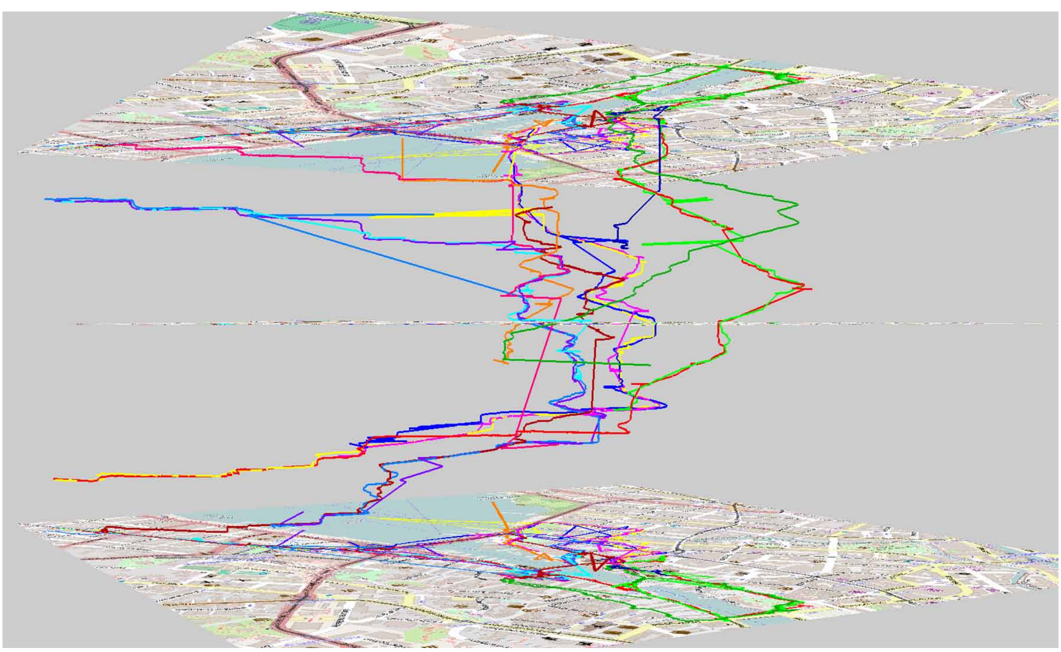
Another misdirection can be found in Figure 12 which displays the same run. By analyzing the learners' tracks in a space-time cube, it became evident that two teams left the study area much earlier compared to all other learners, although they had the task to execute all the learning units. After having arrived at the target location, they solved few tasks independently without conducting the whole round trip, and took public transportation to the way home southwards (to the left border of Figure 12). Interestingly, the orange/magenta team decided to take the same public transportation route as the light-blue/dark-blue/purple/yellow team did a few minutes earlier. Coincidence or purpose, the evaluation reveals this visually by allowing for comparison to other tracks, but does not give the reasons for this early abort, neither for unintentional misdirection nor for deliberate cheating.

DISCUSSION AND OUTLOOK

Advantages and Limitations of Using Visual Analytics

We proposed visual analytics as a spatio-temporal analysis method for teachers to evaluate LBML based on recorded learner trajectories. Visual analytics fosters a hands-on and accessible approach to analyze spatial data. It is based on the fact that human perception is mainly determined by the visual sense (Krygier, 1994). Visual analysis is an intuitive, fast, easy, and efficient technique, and–although we have not tried the methods with teachers yet–we suppose it is intuitive to use for teachers, compared to other (fully-automated) methods which require a deeper understanding of the analysis algorithms and their parameterizations. In addition, visual analytics enables the analyst to explore the data without a hypothesis in mind, but rather with the goal of coming up with a hypothesis, i.e., exploratory data analysis. Future work should investigate these issues further by performing data analysis studies with teachers as analysts.

Figure 12. 3rd Study, "Legends of Zurich": The trajectories of different groups of learners are visualized in a space-time cube. The visualization application allowed orientation by displaying the base map on the ground, at the top, and on an adjustable height depending on the slider's position. Remarkable is that the light-blue/dark-blue/purple/yellow and the orange/magenta team quit the LBML unit early by using public transportation—visible as lines that break away in the upper half to the left (software: © CommonGIS; basemap: © OpenStreetMap)



The visual analytics approach has some limitations that must be taken into consideration. On the one hand, conclusions based on visual analysis require interpretative experience. Moreover, such conclusions are not in every case evident. Furthermore, some aspects of the data are analyzed faster and more reliably with fully-automated approaches than with visual analytics, such as movement trends or travel modes. In this regard, visual analytics will often be the first step which helps in identifying hypotheses and determining which data mining approaches should be used in the second stage.

Another limitation of visual analytics is that, most obviously, visualization per se is accessible only to sighted learners. Furthermore, the human vision processing has limited capacities. For instance, it is not possible for humans to distinguish between 256 different shades of grey, even though the gradient could be rendered (Dambrosio, Amy, & Colombo, 1995). As one alternative approach, an interface for explorative data analysis could address also other senses, such as the auditory sense. Sonification has the potential to make even continuous and fine resolved data accessible to everybody once visualization reaches its limits, or to complement visual perception by utilizing the advantages of multimodality (Schito, 2012).

Environmental Perception and Learning Progress

For teachers, it is difficult to ensure that students demonstrate a learning progress since neither a reliable implementation of this intention can be guaranteed (Borich, 2013) nor classroom assessments provide clear information about the effective learning progress (Dubs, 2009). On the one hand, teachers have an idea which path is most suitable to perceive the impressions used to solve the learning module. However, learners cannot guarantee first, that they keep walking on the path, second, that they perceive the same as the teacher expected, and third, that they really use this particular impression or proposition to build their own knowledge structure. It is arguable whether staying on or leaving the suggested path and thus, freely explore the environment is more or less beneficial for the learning progress. 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 and thus, learning progress more than, for instance, executing single learning units along an instructed path.

Based on constructivism, individual learning is impeded inter alia if the time on task is not exploited optimally (Borich, 2013; Dubs, 2009; Schneider & Stern, 2010). In extreme cases, the time on task is reduced to a minimum if learning units are aborted earlier than expected. Thus, motivation is a key factor to convince learners to take advantage of investing time for learning. However, it was not possible to differentiate between motivated and unmotivated learners or to distinguish a trendsetter by visually analyzing the tracks. Furthermore, the reason why first the light-blue/dark-blue/purple/yellow team all together and shortly thereafter the orange/magenta team shown in Figure 12 took the same public transportation line to go home cannot be explained by visual analysis. If the abort of the learning unit was in fact deliberate, mobile communication might have been a factor that induced the yellow team to abort as well. Thus, mobile communication might impede unrelatedness, however, because mobile communication was not tracked in this context, this hypothesis could be verified.

Consequently, more empirical data and ground truths are needed, perhaps by repeating the outdoor learning units with other participants to verify the indications mentioned, such as post interviews, questionnaires, silent observers (Sailer, Kiefer, Schito, et al., 2015). Furthermore, the explanatory model has to be improved and computational methods as promoted by Laube et al. (2005) must be considered to be taken into account.

Spatio-Temporal Factors of Movement Tracks

The path chosen by learners is highly individual and based on behavior as well as on different decisions made. We propose that the individual paths provide evidence on the learner's uncertainty, time pressure, or (lacking) motivation. The factors distance, duration and speed have been discussed using examples. Further spatio-temporal properties of trajectories are acceleration, deceleration, or curvature. Due to a small sample and the diversity of the positional accuracies of the data caused by different devices, the comparison of different trajectories regarding acceleration and deceleration could not be investigated, but is planned for future work. Assuming that a learner with a distinct target and local knowledge follows the easiest path, curvature might indicate uncertainty in finding the target. Furthermore, straight paths might be an indicator for leaders or motivated learners. Curvy paths alone, however, are not evident to prove uncertainty or a lack of motivation. However, curvature could be combined with deceleration, with the relative position to other learners, or with the time the learner stood still for the purpose of re-orientation or map usage in order to provide evidence about uncertainty or motivation. Third, we assume that learners under time pressure move faster, behave differently, and make more mistakes than regular learners. As Ames (1992) distinguishes between mastery goal achievers and performance goal achievers, time pressure might biasedly foster performance goal achievers who are familiar to deal with pressure. Certainly, our assertions are associated with uncertainty and thus, further research is needed to provide evidence.

Technical Limitations of Positioning Data

Some of our study participants were confronted with technical problems. First, positioning problems occurred, most of them directly after the positioning sensor has been turned on. Some tracks were recorded based on a pseudo-location while the device was searching for satellites. These incorrect points are often recognizable as points on a straight line across the landscape, as for instance in Figure 6, where dotted lines provide evidence for this phenomenon. In general, the accuracy of positioning sensors in older mobile devices is low and thus, uncertainty is high. Therefore, it could be argued that location data collected with mobile devices do not permit conclusions about the learners' behavior. However, teachers using smartphones in their classes must deal with the prevailing technology and thus with the measurement tolerance. Furthermore, to make a statement whether the tasks have been solved or not, the ongoing study has shown that the prevailing measurement tolerance is mostly sufficient.

Comparing Visualizations for Visual Analysis

In this paper, we have always referred in the explanation and interpretation of the figures to direct comparisons, advantages, and disadvantages of analyzing 2D or 3D visualizations. In general, we recommend that teachers analyze recorded paths with interactive and versatile methods. Interactivity supports the individual confrontation of the teacher with the data. Tracks can be shown, hidden, colored, isolated, combined, or animated to emphasize a specific phenomenon. Furthermore, versatile and multimodal methods allow the use of different visual representations and thus address the brain's analyzing capacity not unilaterally (Goldstein, 2014). Moreover, findings are more profound if the tracks are analyzed over time. Thus, time must be visualized somehow: either as slider-controlled animation on 2D maps or as space-time cube in 3D. In this regard, WebGL with the JavaScript libraries d3[4] and threejs[5] currently offers a suitable, easy, and fast option for the implementation of both approaches. An implementation in the web-based OMLETH platform (Sailer, Kiefer, & Raubal, 2015) is planned for future research. However, the storage and access of human movement tracks have to take into consideration privacy issues, even if these tracks are anonymized. Information about personal location is highly dynamic, easily interpretable, and in case of OMLETH available in real-time. Therefore, the cautious and secure usage of these datasets is very important to prevent possible abuse (Duckham & Kulik, 2006; Sailer, Kiefer, Schito, et al., 2015).

Representation of Movement Tracks: Point cloud vs. Line Segments

As mentioned in advance and shown in Figure 7, tracks were at regular time intervals. The simplest way to visualize these discrete records are points—basically visualized or temporally animated. Such point clouds indicate an area of specific interest without displaying wandering learners noisily. In fact, however, tracks of goal-directed learners are continuous, thus, it seems obvious to connect two chronologically consecutive records with an interpolated line segment and visualize them as trajectories to clarify the chronological sequence (G. Andrienko et al., 2013). Interpolated line segments, however, are always only an approximation of the real trajectory. The inaccuracy of trajectories can be large if the temporal recording frequency is low. Furthermore, the visualization of interpolated line segments visually covers space which may increase cognitive load. We argue that the visual analysis is too complex and could distract the reader from the map analysis if overlying lines cover underlying lines with a strong informative content. Instead, blending unnecessary lines out, or, making unimportant lines more transparent, brighter, or thinner reduces graphical overload. Because both approaches have advantages and disadvantages, an evaluator must decide which shall be used for which purpose.

2D vs. 3D Environment Limitations for Visual Analytics

Because many teachers have experience in interpreting common 2D maps and because online map services prevalently start in a 2D view, we also recommend to teachers to start visual analysis in 2D. First actions usually include comparing the map-based context of the direct neighborhood where 2D might be faster than 3D. Design errors, ideal path deviations or other phenomena can be determined efficiently in 2D.

The 3D space-time cube appears to be more suitable for identifying the behavior of moving objects over the whole time duration compared to 2D animated representation. Although the perspective view of the space-time cube can be interactively changed, (G. Andrienko et al., 2013) argued that this technique is not very convenient for location trajectory segments in space and time because interaction such as zooming, panning, and rotating through the 3D interface has to be learned. Furthermore, information retrieval (e.g., time, duration, spots, content) might be challenging due to spatial distortion and complex perception even if an additional time scale is visualized. Therefore, it is recommendable to add further informative elements to the map, e.g., graphs, speed graph, travelled distance, or suggested clusters techniques (G. Andrienko et al., 2013). In general, 3D analysis is more complex than 2D analysis and requires more experience in applying spatial analysis techniques used in the field of GIS.

In conclusion, to investigate whether 2D or 3D representations are preferred, further exploratory studies with teachers in a real environment need to be conducted. We expect that the spatial cognition and spatial abilities of teachers are crucial in designing LBML modules (Sailer, Schito, et al., 2015). We argue that the visual analytics of movement tracks after an executed learning module needs at least the same amount of spatial cognition skills as the design part of the learning units.

Advantages of Visual Analysis for Teaching

At least as important as the class planning is the post-hoc reflection of general or specific things that could be done better next time. The aim should be to offer learners a learning-supportive environment (Borich, 2013) and to implement findings from the field of learning research to exploit learning capacities optimally. In this regard, a reflective learning unit follow-up fosters improvement in teaching. Thus, the visual analysis of the learning unit can be seen as an analytical part of the follow-up with the goal of investigating things that went well or not well and to find solutions, how they could be improved in the future. If the time on task at one specific site was low, solutions should be found how it could be increased to address cognitive learning better than in past classes. In accordance with Schito, Sailer, and Kiefer (2015), the resulting learning unit including the tasks is based partly on experience. We believe that especially the findings of the follow-up raise teacher's experience to plan future classes smoothly and thus, encourage teachers to attach importance to embed visual analysis for the follow-up.

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ENDNOTES

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Christian Sailer is a research assistant at the Geoinformation Engineering group, ETH Zurich. He received his Master of Science in Geography from the University of Zurich, Switzerland, in 2008. He has been working since 2006 at Esri Switzerland and was in charge of customers from Education and Environment. In his current research at ETH, he develops a platform for location-based mobile learning to research the use in higher education. He is specifically interested in both, teaching and technologies that can teachers as well as learners help to improve the interaction with mobile learning services.

Peter Kiefer is a senior research assistant at the Geoinformation Engineering group, ETH Zurich. He received his PhD (Dr. rer.nat.) in Applied Computer Science from the University of Bamberg, Germany, in 2011. In his current research he investigates people's attention and intentions while using mobile GIS and location-based services. He is specifically interested in new assistive technologies that can help to improve the interaction with mobile geo-spatial services.

Joram Schito is a research assistant at the Geoinformation Engineering group, ETH Zurich. He received his Master of Science in Geography from the University of Zurich, Switzerland, in 2013 with distinction for his Master's Thesis in GIScience. Joram is qualified teacher of geography and general education and has broad experience in teaching at secondary and tertiary level. In his current research he develops new approaches to calculate the route and to estimate the costs of electric power systems. He is specifically interested in spatial data analysis and in developing new methods to optimize data perception.

Martin Raubal is Professor of Geoinformation Engineering at the Swiss Federal Institute of Technology (ETH) Zurich. He was previously Associate Professor and Vice-Chair at the Department of Geography, University of California, Santa Barbara. Martin received his PhD in Geoinformation from Vienna University of Technology in 2001 with honors. His research interests lie in the areas of Mobility & Energy, more specifically in mobile GIS & LBS, spatial cognitive engineering, mobile eye-tracking, and GIS for renewable energy analysis. Martin is currently Co-Chair of AGILE (Association of Geographic Information Laboratories in Europe). He serves as Associate Editor of the Journal of Location Based Services, and on the editorial boards of Transactions in GIS, Journal of Spatial Information Science, Spatial Cognition and Computation, and Geography Compass. He has authored and co-authored more than 100 books and research papers published in refereed journals and conference proceedings.