Geogames - Intention recognition and data quality in location-based gaming

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1 Introduction

Mobility is often regarded as a necessity we cannot avoid due to professional and private activities in our daily lives. Waiting for the train, being trapped in a traffic jam, and the like, are generally perceived as time-consuming and enervating. Mobile computing has opened a bunch of new possibilities for entertainment which can help us to make the best of our journey. Mobile phone games and mobile TV (e.g. [9]) are typical examples. Most of these systems try to port a stationary entertainment experience to a mobile device. The spatio-temporal movement is seen as an unavoidable precondition for which we must find a technical solution, but not as an entertaining element itself.

Exactly this issue is addressed by *location-based games* (LBG), which take use of positioning technology (e.g. GPS) and integrate the player's position into the logics of a game [11]. This approach of not only creating entertainment *for* mobility, but also creating entertainment *from* mobility seems quite promising. Projects in the pervasive gaming community have proposed a number of LBGs [3], and addressed various research questions. However, the AI aspects connected with LBGs have largely been ignored.

The Geogames project aims at exploring how methods from AI can be used in all phases of a LBG: before, during, and after the game. The research directions addressed in the project follow these three phases. We are especially interested in the implications of space and time on AI in LBGs. The following questions guide our research:

1. *Game design and setup*: how can we create a game that addresses both, the player's intellectual and sportive skills? How does the choice of geographic footprints influence the spatio-temporal flow of a game? And, closely related: how can we help the game designer to port a game to a new geographic area? (section 2)
2. *During the game*: how can we infer the player's intentions to act from her spatio-temporal behavior (*mobile intention recognition*)? How can we model complex connections between intentions, space, and time? How can we use the spatial context to make the inference process more efficient? (section 3)
3. *After the game*: how can the spatial data collected during the game help us to improve geographic data quality? Can we use LBGs for the community-based collection of geographic data? (section 4)

In this project report we will only shortly review the main findings of the first research direction and then concentrate on the current project phase which is concerned with the second and third. These two directions are closely related to ongoing PhD research projects. We present the central findings of previous and current work, and conclude our report in section 5.

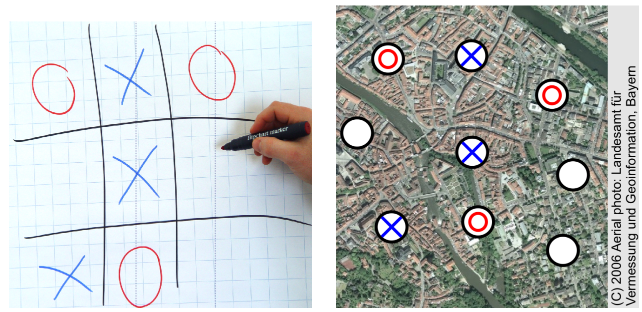

Figure 1: Board game Tic Tac Toe (left) and the spatialized version GeoTicTacToe (right)

2 AI support during game design and setup

Game creators tend to have a metaphor in mind when conceiving a new game. While other LBGs follow metaphors like arcade games or catch games (PacManhattan, Can You See Me Now, see [3]), the Geogames project creates games from the metaphor of traditional board games. The strategic elements of the board game are combined with the sportive challenge of moving in a city. Geogames define not only a single game but a whole class of LBGs.

The simplest example of a Geogame is GeoTicTacToe, a location-based variant of Tic Tac Toe (see Fig. 1). In Schlieder et al. [21] we explained why it is not trivial to bring a board game to the real world: due to the real-time nature of gameplay, trivial strategies that support pure race games are possible. We call this the *synchronization problem*. We showed that a temporal solution to this problem exists: players are forced to wait a certain amount of time (synchronization time) after each move before they are allowed to change their position.

But why do we need AI research in this context? The game creator has several parameters she needs to adjust for a specific game: regarding the spatial parameters, she has to decide about the size of the gaming area, and the spatial layout of the relevant coordinates. Obstacles, road network, and elevation profile must be considered. With respect to the temporal parameters, she must select an appropriate synchronization time interval. Testing an arbitrary number of possible configurations in the real world is not possible, for organizing and playing a LBG takes quite some time and effort. Thus, tool support for configuring the game parameters beforehand is desired. The Geogames Tool [21] offers the possibility to compute an optimal synchronization time interval for any spatial layout of the game. The tool is working with a variant of the well-known MinMax algorithm, adapted to spatio-temporal problems. The alternating turns of a traditional MinMax tree are replaced by a spatio-temporal mechanism for deciding who will do the next move. With the Geogames tool, porting a Geogame (like GeoTicTacToe) from one geographic location to another becomes an easy task.

The choice of the spatial parameters becomes even more complicated if we allow the adversary teams to be located in different cities [12]. Here, another parameter becomes important: the logical identification of game-relevant coordinates.

A thorough reader may have noticed that games like GeoTicTacToe allow (and also require) players to move freely in the gaming area. In contrast, an entertainment solution for commuters, like sketched in the introduction, must support route-based movement with only few degrees of freedom. This kind of games has been explored under the title of 'backseat gaming' (e.g. [2]). 'Linear' LBGs with an emphasis on strategic game play have been developed in the Geogames project, see GeoAlak [10] and the FluPa-game [13]. The configuration problems described above apply for these games in a similar way.

3 Mobile Intention Recognition: AI support during the game

Players in a LBG move at high speed and focus on several other tasks besides gaming. Current mobile devices are rather small and difficult to handle under such conditions. Similar situations occur in non-gaming areas, like maintenance work or car navigation. If we were able to read the player's thoughts we could offer her an appropriate information service automatically. Instead, we try to infer the player's intentions from her (spatio-temporal) behavior (*mobile intention recognition*). In literature, intention recognition is also known as *plan recognition* (see [5] for an overview). In difference to traditional applications of plan recognition, like language and story understanding, mobile behavior happens in space. The computational resources of mobile devices are restricted, and the context changes rapidly.

The most commonly used type of context is position. Our gaming device in the FluPa-game could automatically offer us a map at detailed zoom level if we enter a region of type 'village' (see Fig. 2). Many location-based services map the user's position directly to a information service. There are situations where this can lead to an undesirable information push: as soon as the player in Fig. 2 starts to cross village_2, we present him a detailed map although he is not specifically interested in that region (*room-crossing problem*, see [20]). Our first contribution to the problem of mobile intention recognition is an architecture that introduces two layers ('behaviors' and 'intentions') between the position and the information service, like displayed in Fig. 2. A pattern recognition mechanism produces a stream of behaviors which is processed by an intention recognition mechanism in the next step. The current intention is mapped to an information service.

Our second interest is the intention recognition mechanism itself. Intention recognition in its general form is known to be intractable. Tractable special cases of the problem are therefore of great practical interest. The idea is to model not only the intentions in a certain domain, but also the connection between intentions and space: which intention can occur in which spatial region? By using this knowledge the intention recognition

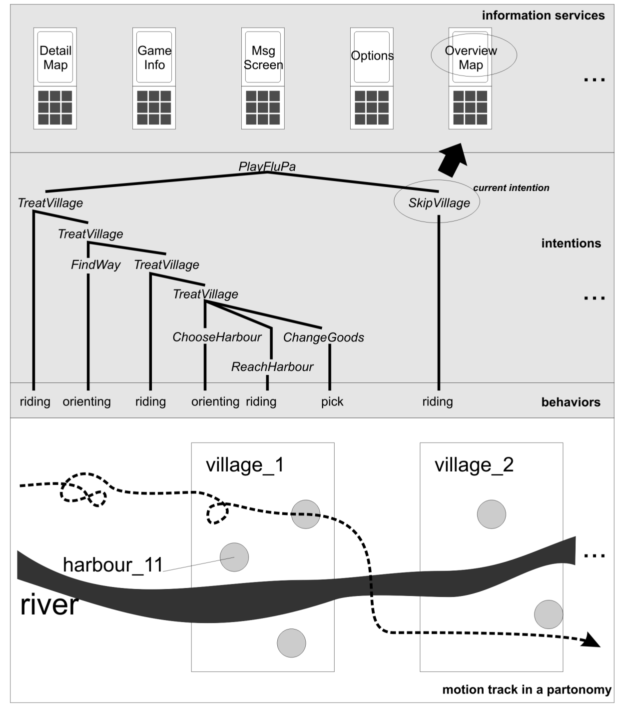

Figure 2: Motion track, behavior sequence, and grammatical intention recognition in a location-based game.

algorithm can prune those hypotheses about possible intentions that are not consistent with the spatial context.

We use formal grammars to model intentions so that intention recognition becomes a parsing problem. With formal grammars the connection between expressiveness and complexity becomes explicit. In [20], we have presented *spatially grounded intentional systems*, a representational formalism based on context-free grammars (CFG) that takes use of spatial knowledge. CFGs are known to be efficiently parsable and intuitively understandable during model creation. Not displayed in Fig. 2 is the spatial grounding of rules. Each rule in an SGIS is only applicable in a certain set of regions. Thus, the parsing mechanism does not need to check any rule at any position in space, which reduces parsing ambiguities. For instance, the rule $TreatVillage \rightarrow ChooseHarbour\ ReachHarbour\ ChangeGoods$ is only applicable in regions of type 'village'.

In some domains, context-free rules may not be expressive enough. In recent work we have discussed the use of mildly context-sensitive grammars for intention recognition [13]. These are grammars developed in the natural language processing community which are still polynomially parsable. A similar argument is made in [7], but not for mobile systems. We are currently developing a new formalism, *Spatially Constrained Tree-Adjoining Grammars*, that allows to formalize complex constraints between intentions and space. As future work we will evaluate if parsing our spatially constrained grammars is feasible on mobile phones.

Recent work in the field of plan recognition has mostly used probabilistic network based approaches (Bayesian approaches, [6]). One approach chooses a Hierachical Markov Model and Particle Filtering to predict a user's changes in transportation mode, like getting on or off a bus [14]. Another probabilistic network based approach, the Abstract Hidden Markov Model, is chosen by [4]. Both systems send the collected data to a server which does the computations. In contrast, we target at on-device computations and believe that there is a need for stand-alone mobile intention recognition, given the incomplete covering of low-cost data transfer possibilities, and privacy issues.

4 Spatial Data Quality: AI support after the game

In the course of the above discussed intention recognition approach a considerable amount of geographic data is logged during the course of a game. This data is not only useful to provide the player with an intelligent user interfaces but can be of use when the game is long over.

As we have seen, the main game element in a LBG is the locomotion of the player in the real world. Players are equipped with some kind of mobile device using some sort of localization technology to determine the position of the player in the games. With such a device players are capable of saving geospatial data during the course of a game, turning them into "voluntary sensors" [8]. The idea to motivate communities of non-experts to provide data that are hard to acquire otherwise has been already conducted successfully with a browser game by von Ahn and Debbish [1]. They used their ESP game to gather semantic tags for images found in the World Wide Web. For the location-based gaming domain a similar approach was proposed by Matyas (2007) [15].

But why do we need AI research when the wanted geospatial data are already provided freely by a community of players? Traditionally geographic and semantic data about the real world is collected by expert data collectors. Using such experts has the advantage that the quality of the data is known in advance. In contrast, the quality of the data acquired by the participating non-experts in a LBG can at best be qualified as being unknown. It is this disadvantage that we want to address by using techniques from semantic information and spatial data processing. The basic idea consists in aggregating data inputs of as many users as possible to increase the size of data sample and, ultimately, the quality of the result.

The aggregation problem for collaboratively collected geospatial data has two facets: the spatial and the semantic aggregation problem. With point of interest (POI) data, the spatial problem amounts to aggregate several measurements of the geographic position of a POI. Spatial averaging based on reasonable assumptions about the positional error distribution will solve this problem. In a similar way, positional data about higher-dimensional features is approached. Morris et al. [17], for example, suggest methods for the aggregation of 2D line features. However, the issue of which measurements actually refer to the same feature is more complex as it involves feature type semantics.

Consider the following example: In Figure 3 two GPS tracks are shown, which represent bicycle tours recorded by two different tourists playing the FluPa game [13] along the Regnitz river. One was taking the route along the left bank of the Regnitz river (track_1), the other the route on the right bank (track_2). Both tourists submit their data after the game to a related website.

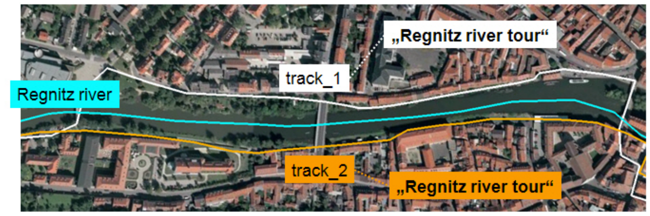

Figure 3: Spatial data gathered and categorized (as *River Regnitz tour*) by two biking tourists, © aerial photo: Google Earth (http://earth.google.com/).

We assume that the spatial data describing the course of the Regnitz river is already part of the data set. It could have been computed, for instance, from tracks entered by canoe tourists. A simple spatial aggregation algorithm such as the one proposed in [19] would just interpolate between the two biking tracks by constructing a line of points with equal distance to each of the two tracks. However, the resulting track would end up in the middle of the river, thereby producing a semantic conflict. A semantic conflict situation is described in form of a rule: the result of spatial aggregation of biking trails may not lie within a water body.

Typically, the data collected for a POI or a higher-dimensional spatial feature associates positional information (e.g. lat/long) with information about the feature type (e.g. restaurant). A comprehensive solution of the data aggregation problem needs a combined approach which takes both, the spatial as well as the semantic data into account. Our first approach to solve this problem consists of two steps: The definition of preconditions in form of rules and the definition of an actual aggregation method.

In the first step we use a simple relational language that augments spatial SQL relations by constructs from formal ontologies which permit to specify type information for the relation's arguments. A relational statement makes an assertion about a spatial or semantic relation that holds between geographic objects of a certain type. The language permits the modeling of both distance relations (e.g. *small_distance*) and directional relations encoding ordering information (e.g. *between*) besides the traditional spatial SQL relations (e.g. *intersects*).

If data sets are found that are checked positively against defined precondition rules, an data aggregation algorithm like the one of Morris et al. (2004) [17] is used to aggregate the geospatial data.

A first formalization of the language can be found in [16]. Currently we are working on the specification of new aggregation methods that take the semantic data into account also in the actual aggregation step and not only in the precondition statements.

5 Conclusion and Outlook

The research in the Geogames project has opened a new perspective on LBGs. At the same time, the methods developed in the scope of this project are of interest for a larger AI community as they can be applied for non-gaming scenarios. As future work we continue with our research in each of the three research directions, as mentioned in each section. As well we plan to explore the possibilities of combining the three directions. For instance, the data aggregation process described in section 4 can provide input data for the geographic model needed for mobile intention recognition.

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