Time Geography Inverted: Recognizing Intentions in Space and Time

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ABSTRACT

Mobile intention recognition is the problem of inferring a mobile user's intentions from her behavior in geographic space. Such behavior is constrained in space and time. Current approaches, however, have difficulties to handle temporal constraints. We therefore propose using the framework of time geography to formalize and visualize both spatial and temporal constraints for the mobile intention recognition problem. A new rule language is introduced which allows for modeling intentions with spatial and temporal constraints. A location-based game application demonstrates that interpreting a user's spatio-temporal behavior sequence in terms of intentions reduces ambiguity compared to mobile intention recognition without temporal constraints.

Categories and Subject Descriptors

H.2.8 [**Database Applications**]: Spatial databases and GIS; I.2.4 [**Artificial Intelligence**]: Knowledge Representation Formalisms and Methods

Keywords

Spatio-temporal Behavior, Intention Recognition, Time Geography, Rule Language, Mobile Systems

1. INTRODUCTION

The widespread integration of positioning technologies into mobile devices has lead to an increased interest in processing, analyzing, and interpreting human behavior in geographic space. Spatio-temporal data mining systems, for instance, analyze large amounts of motion track data to detect interesting patterns, such as flocking behavior [8] or user similarity [10]. On the other hand, the analysis of an individual's motion track helps to provide better location-based assistance [6].

In both application areas, tasks need to be solved on three semantic levels. On the lowest level, a geometric analysis regards the spatio-temporal properties of one or several motion tracks (e.g., [17]). On the next semantic level, approaches interpret the trajectory using a geo-model of interesting locations. Simple location-based services that map a user's position to an appropriate information service are one typical example. *Intention recognition* (IRec), the highest semantic level, assigns a meaning (in terms of user intentions) to the behavioral data. This allows us to resolve ambiguities that occur if a location offers several possible activities, and if the user enters a location accidentally. It can enhance intelligent location-based services that proactively assist their users based on their behavior.

IRec is based on a model of the user and the domain. In particular, the intentions a mobile user can have in a certain situation are constrained by space and time. While current approaches for mobile IRec are able to handle spatial constraints [16], the temporal aspects have largely been ignored. However, it is clear that temporal constraints can help to reduce ambiguity. For instance, the time of the day may help us to decide whether the visitor of a shopping mall has the intention to go shopping or to the movies located in the same building. Temporal constraints such as these are the core idea of the time-geographic framework [3]. Although time geography and mobile IRec share these common ideas, time geography in the context of mobile assistance has so far only been considered for the planning problem, which is the inverse problem of IRec (e.g., [14]). The planning problem has an intrinsic complexity that makes it challenging to find efficient algorithmic solutions. In contrast, efficient algorithmic solutions exist for IRec.

In this paper, we propose a new conceptual view on the mobile IRec problem. We relate concepts from time geography and IRec to each other and introduce a rule-based formalism in order to model the complex relations between space, time, and intentions (section 3). An algorithmic solution for the mobile IRec problem reduces interpretation ambiguities through spatial and temporal disambiguation. An evaluation with the location-based game CityPoker shows how the spatio-temporal constraints reduce ambiguity, compared to formalisms without temporal constraints (section 4).

2. RELATED WORK

Approaches to IRec differ in the way the domain and intentions are represented. While formalisms based on finite-state machines [1] are not sufficiently expressive for many domains, too general formalisms lack efficient algorithmic solutions [4]. Probabilistic network based approaches, like [11], come with a previously learned model that is cognitively difficult to understand for humans. In mobile assistance we often need to rewrite or modify

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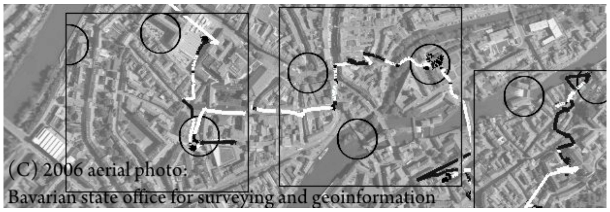

Figure 1: Spatial structure and motion track in CityPoker.

the knowledge base to port the system to a new area. This is much easier with formal grammars, like Probabilistic State-Dependent Grammars [13] (PSDG). However, as PSDG are not specifically designed for spatio-temporal knowledge, inference may become intractable.

Spatially-Grounded Intentional Systems (SGIS) are a formal grammar specifically designed for spatial behavior [16]. An SGIS is a context-free grammar (CFG) on behaviors and intentions, enhanced with spatial constraints. The idea of SGIS is to reduce parsing ambiguities by making the applicability of rules dependent on the space where the behavior occurs. *Spatially-Constrained Tree-Adjoining Grammars* (SCTAG) are a spatial formal grammar that additionally allows to model long-ranging and crossing dependencies between the regions in a long behavior sequence [5] .

Time geography defines the space-time mechanics of locational presence by taking into account different constraints that limit a person's activities in space and time [3]. The possibility of being present at a specific spatio-temporal location (*space-time station*) is determined by the person's ability to trade time for space. Fundamental physical restrictions on abilities and resources are summarized as *capability* constraints. *Coupling* constraints refer to the requirement for a person to be at a specific location at a certain time or during a specific time interval. Certain domains in life are controlled by *authority* constraints, e.g., a person can only shop at a mall when the mall is open. *Space-time paths* illustrate the movement of individual agents in space over time. All space-time paths must lie within *space-time prisms* (STP), geometrical constructs of two intersecting cones [9].

Time geography has been applied in the area of Geographic Information Systems (GIS) to model and measure space-time accessibility in transportation networks [15], and for the analysis and theoretical understanding of disaggregate human spatial behavior [7]. It has also been advocated to integrate time geography with both GIS and location-based services (LBS) to achieve more user-centered systems [14]. Analytical formulations of basic entities and relationships from time geography can be found in [12].

Production Rules		***Grounding***	
PlayCP →	*DiscussStrategy Play ReturnHome EvaluateHands*	R_{game}	*(1)*
DiscussStrategy →	b_0	R_{start}	*(2)*
Play →	*ChangeInRegion Play* |	R_{game}	*(3)*
	ChangeInRegion	R_{game}	*(4)*
ReturnHome →	$(b_r \| b_c)^+$	R_{game}	*(5)*
EvaluateHands →	b_0	R_{start}	*(6)*
ChangeInRegion →	*FindRegion HandleRegion*	R_{game}	*(7)*
FindRegion →	$(b_r \| b_c \| b_0)^+$	R_{game}	*(8)*
HandleRegion →	*SelectCache GotoCache GetCard*	$R_1 \dots R_5$	*(9)*
SelectCache →	*FindParkingPos SolveQuiz*	$R_1 \dots R_5$	*(10)*
FindParkingPos →	b_r	$R_1 \dots R_5$	*(11)*
SolveQuiz →	b_0	$R_1 \dots R_5$	*(12)*
GotoCache →	*ApproachCache GotoCache* |	$R_1 \dots R_5$	*(13)*
	OrientToCache GotoCache | ε	$R_1 \dots R_5$	*(14)*
ApproachCache →	$(b_r \| b_c)^+$	$R_1 \dots R_5$	*(15)*
OrientToCache →	$(b_s \| b_{sc} \| b_0)^+$	$R_1 \dots R_5$	*(16)*
GetCard →	*SearchCard* |	R_{11} ... R_{53}	*(17)*
	SearchCard b_0	R_{11} ... R_{53}	*(18)*
SearchCard →	*RoamCache SearchCard* |	R_{11} ... R_{53}	*(19)*
	DetailSearch SearchCard | ε	R_{11} ... R_{53}	*(20)*
RoamCache →	$(b_r)^+$	R_{11} ... R_{53}	*(21)*
DetailSearch →	$(b_c \| b_s \| b_{sc} \| b_0)^+$	R_{11} ... R_{53}	*(22)*

Figure 2: SGIS production rules for CityPoker.

3. TIME GEOGRAPHY AND INTENTION RECOGNITION

3.1 The CityPoker Scenario

CityPoker is a location-based game played by two opposing teams in an urban environment. It is typically played at high speed on a bike which restricts interaction possibilities with a mobile assistance system. We use this game as a test case for mobile IRec because it is easy to experiment with different rule sets in a game. The idea of the game is to improve one's poker hand by finding and changing hidden cards. This includes solving multiple-choice quizzes and a detailed search in the environment. The game takes place in a set of spatial regions: the game area (R_{game}) contains five disjunct rectangular cache regions ($R_1, \dots, R_5$), each of which contains three disjunct circular caches ($R_{11}, \dots, R_{53}$). The game starts and ends in the start region (R_{start}). Figure 1 illustrates a typical motion track and part of the partonomy. There is an overall time limit to the game, within which the teams must return to their starting position. The rules are described in more detail in [16]. We can model a team's behavior with the SGIS production rules displayed in Fig. 2. Depending on the spatio-temporal properties of motion track segments, we distinguish the behaviors riding (b_r), searching (b_s), curving (b_c), slow curving (b_{sc}), and standing (b_0) (details on the pre-processing are given in [6]). Some rules are applicable in the five cache regions, others are applicable in the 15 caches. Recognizing intentions in CityPoker means assigning one intention to each behavior in a spatialized behavior sequence. With SGIS, this problem becomes a problem of parsing. The current intention for each spatialized behavior is the direct parent node in the parse tree. The mobile assistance system maps the current intention to an information service and presents it to the user.

3.2 The Inverse Problem of Time Geographic Planning

Research on time geography for mobile assistance has been centered around questions of planning. For instance, what is the optimal plan of a mobile user who wants to perform a set of actions, given capability, authority, and coupling constraints [14]? The output of the planning problem is an ordered sequence of (action, station) pairs, including the shortest path and preferred means of transportation to travel between these stations. Mobile assistance systems building on intention recognition solve a different problem. Instead of letting the user specify her intentions beforehand and proposing an optimal plan, these systems try to infer the user's intentions by observing her behavior on-the-fly.

We illustrate the IRec problem for CityPoker with a time geographic visualization (Fig. 3): the agent is located in the gaming

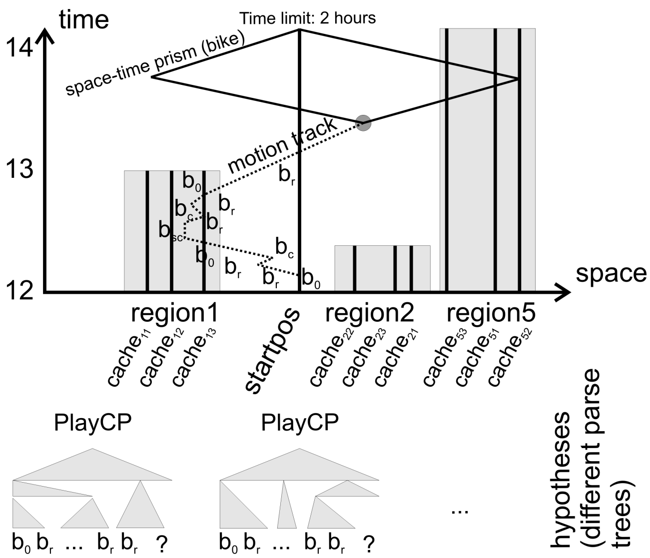

Figure 3: A time geographic visualization of intention recognition in CityPoker.

area and we do not know her current and future intentions. However, we have collected her motion track history and thus know the stations she has visited. There she has probably had some of the intentions these stations afford, but we do not know which ones. In particular, we do not know if the agent had an intention afforded by a region itself, or by one of the parent regions in the partonomy. For instance, if the agent crosses a cache, this may also happen accidentally while having an intention afforded by the enclosing cache region. We compute a behavior sequence using the spatio-temporal characteristics of the track and try to interpret it using production rules of a grammar, grouping behaviors to intentions, intentions to super-intentions, until we reach the top-level intention *PlayCP*. This grouping problem can efficiently be solved with parsing algorithms. If more than one grouping is possible, we have an ambiguous behavior sequence, i.e., several possible parse trees. If these possible parse trees differ in their current intention we have several hypotheses.

Grammars that include spatial and/or temporal knowledge can help us to reduce the number of possible hypotheses. *Spatial disambiguation*, as supported by SGIS, appears if production rules cannot be applied because at least one of the leaf node behaviors in the parse tree is not in one of the regions in which the rule is grounded. Using time geographic concepts we may achieve three further types of disambiguation: 1) *Time slot disambiguation*: a production cannot be applied because of the current time. In CityPoker a cache region might be authority constrained between 1 and 3p.m. 2) *Durational disambiguation*: a production rule can no more be applied because the agent showed a certain behavior sequence for too short or too long. In CityPoker this may happen if the behaviors of a *DetailSearch* take too long, and thus the user has probably changed her strategy. 3) *Capability disambiguation*: a hypothetical parse tree requires the agent to be in a certain region at a certain time in the future, but the agent will never make it on time because of her capability constraints. In the following, we introduce a new grammar formalism that allows for spatial, time slot, and durational disambiguation.

Authority Constraints (*ac*)		
Region	Timeslot	Duration
R_1	[8a.m.; 1p.m.]	$]0;+\infty[$
R_1	[3p.m.; 10p.m.]	$]0;+\infty[$
R_2	[6a.m.; 12:30p.m.]	$]0;+\infty[$
R_2	[2:30p.m.; 10p.m.]	$]0;+\infty[$
R_5	[6a.m.; 4p.m.]	$]0;+\infty[$
Temporal Constraints (*tc*)		
Rule	Timeslot	Duration
(1)	$[6a.m.;10p.m.]$	$[30min;120min]$
(2)	$]-\infty;+\infty[$	$[5min;30min]$
(12)	$]-\infty;+\infty[$	$[2min;5min]$
(17)	$]-\infty;+\infty[$	$[2min;20min]$
(18)	$]-\infty;+\infty[$	$[2min;20min]$

Figure 4: A TR-SGIS for CityPoker (extending Fig. 2).

3.3 TR-SGIS: An Intention Recognition Grammar With Spatio-Temporal Knowledge

Each SGIS rule is constrained to a set of points in two-dimensional space $\mathbb{R}^2$. Adding temporal constraints means adding a third dimension ($\mathbb{R}^3$). In practice, spatial constraints are not expressed as general point-clouds in $\mathbb{R}^2$, but related to a given geo-model (regions). Accordingly, we express temporal constraints as intervals on a time scale. We also include durational constraints (intervals with minimum and maximum duration). A given behavior sequence may, for example, be interpreted as $DrinkCocktails$ or $HaveDinner$, depending on the duration of all terminal behaviors. Based on these considerations we define:

A temporally restricted and spatially grounded intentional system is a production system TR-SGIS = (B, I, S, P, R, cap, con) with B (set of behaviors = terminals), I (set of intentions = non terminals), S (top level intention = start symbol), P (productions rules), R (set of regions) defined as in SGIS. Capabilities assign each coordinate and region the shortest time the agent will need to travel between them. Constraints $con = (sc, ac, tc, stc)$ constrain the applicability of the production rules: *Spatial constraints* restrict the applicability of a rule to certain regions (as in SGIS), $sc \subseteq P \times R$. For instance, in CityPoker teams can only change a card in one of the caches. *Authority constraints* restrict the accessibility of a region to certain time slots and certain duration intervals, $ac \subseteq R \times T \times (\mathbb{R} \times \mathbb{R})$. For instance, in CityPoker teams can only act in cache regions that are currently open to the public. We can also imagine durational authority constraints, such as 75 minutes parking signs that define the maximum time you are allowed to stay in that parking area. *Temporal constraints* restrict the applicability of a rule to certain time slots and certain duration intervals, $tc \subseteq P \times T \times (\mathbb{R} \times \mathbb{R})$. For instance, we can assume that CityPoker is played only during daytime and with a duration between half an hour and two hours. *Spatio-temporal constraints* are those constraints that are dependent on all three dimensions and cannot be expressed with sc, ac, or tc: $stc \subseteq P \times R \times T \times (\mathbb{R} \times \mathbb{R})$

Figure 4 extends the SGIS example from Fig. 2 and shows how a TR-SGIS could look like for CityPoker. Spatial constraints are already included in the 'Grounding' column of Fig. 2. Capabilities cap are not displayed, but may be computed from travel distances (on a road network) and the player's speed.

#	input	ambig.	#	input behavior	ambig.
1	(b_0, R_{start}, 13:00)	(1, 1, 1)	16	(b_r, R_3, 13:38)	(2, 2, 2)
2	(b_r, R_{game}, 13:15)	(1, 1, 1)	17	(b_{sc}, R_3, 13:39)	(2, 1, 1)
3	(b_c, R_{game}, 13:17)	(1, 1, 1)	18	(b_s, R_{31}, 13:40)	(2, 2, 2)
4	(b_r, R_{game}, 13:19)	(2, 1, 1)	19	(b_r, R_3, 13:41)	(4, 3, 1)
5	(b_c, R_{game}, 13:21)	(1, 1, 1)	20	(b_0, R_3, 13:42)	(5, 2, 1)
6	(b_r, R_{game}, 13:23)	(2, 1, 1)	21	(b_c, R_3, 13:43)	(4, 2, 1)
7	(b_r, R_1, 13:25)	(2, 2, 1)	22	(b_r, R_3, 13:44)	(5, 3, 1)
8	(b_r, R_{12}, 13:27)	(2, 2, 1)	23	(b_0, R_{33}, 13:45)	(6, 4, 2)
9	(b_r, R_1, 13:29)	(2, 2, 1)	24	(b_{sc}, R_{33}, 13:46)	(2, 2, 2)
10	(b_c, R_{game}, 13:31)	(1, 1, 1)	25	(b_0, R_{33}, 13:47)	(4, 4, 4)
11	(b_r, R_{game}, 13:32)	(2, 1, 1)	26	(b_r, R_{33}, 13:48)	(4, 4, 4)
12	(b_c, R_{game}, 13:33)	(1, 1, 1)	27	(b_s, R_{33}, 13:49)	(2, 2, 2)
13	(b_r, R_{game}, 13:34)	(2, 1, 1)	28	(b_0, R_{33}, 13:50)	(4, 4, 4)
14	(b_r, R_{32}, 13:35)	(2, 2, 2)	29	(b_r, R_3, 13:51)	(4, 3, 3)
15	(b_0, R_{32}, 13:36)	(2, 2, 2)	30	(b_r, R_3, 13:52)	(5, 4, 4)

Figure 5: Behavior sequence in CityPoker with ambiguity values for three formalisms (CFG, SGIS, TR-SGIS).

4. EVALUATION

We evaluate TR-SGIS with a behavior sequence from a real CityPoker game session ((behavior, region, time) triples in Fig. 5). Behaviors have been annotated manually, in order to avoid preprocessing errors. We extend Earley's well-known CFG state-chart parser [2] to TR-SGIS parsing. The output is a stream of sets of intentions. If a set contains more than one intention the according behavior is ambiguous. The size of the set indicates the degree of ambiguity. We use the production rules and constraints from Figs. 2 and 4.

The ambiguity values in Fig. 5 for the three incremental algorithms (CFG, SGIS, TR-SGIS) show that the location information of SGIS strongly reduces the ambiguity compared to CFG parsing. TR-SGIS reduces ambiguity whenever temporal constraints apply: for instance, the input with indices 7 to 9 has a reduced ambiguity because TR-SGIS can exploit the knowledge that R_1 is not accessible at that time (time slot disambiguation). This qualitative analysis of the disambiguation capabilities is confirmed by a quantitative analysis that compares the number of output sets that are non-ambiguous. CFG has 6 (20%), SGIS has 11 (37%), and TR-SGIS has 18 (60%). This demonstrates that disambiguation relying on temporal contraints is not just a theoretical option but an effective strategy for dealing with empirical behavior sequences.

5. CONCLUSION AND OUTLOOK

We have introduced the idea of using concepts from time geography to model mobile intention recognition problems. For recognizing a user's intentions the system needs a model of spatio-temporal behavior in the application domain. We have presented a new formal grammar, TR-SGIS, that allows us to elegantly model spatial and temporal constraints. Results of interpreting an empirical behavior sequence from CityPoker show how spatio-temporal constraints reduce ambiguity, compared to unconstrained and only spatially constrained formalisms. We expect that mobile assistance systems implementing 'intention-aware' services can better predict their users' information needs than those using simple location-based services. Part of our future work is the portation of TR-SGIS to other location-based services, such as tourist or exhibition guides. We chose a game as an example here because it allowed us to easily change the rule-sets and geographic embedding. From a conceptual point of view, we will consider the integration of temporal constraints in the SCTAG formalism [5].

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6. REFERENCES

[1] D. Ashbrook and T. Starner. Learning significant locations and predicting user movement with GPS. In *Proc. of IEEE 6th Int. Symposium on Wearable Computing*, 2002.

[2] J. Earley. An efficient context-free parsing algorithm. *Communications of the ACM*, 13(2):94–102, 1970.

[3] T. Hägerstrand. What about people in regional science? In *Papers of the Regional Science Association*, pages 7–21, 1970.

[4] H. A. Kautz. *A Formal Theory of Plan Recognition*. PhD thesis, University of Rochester, Rochester, NY, 1987.

[5] P. Kiefer. Spatially constrained grammars for mobile intention recognition. In C. Freksa, N. S. Newcombe, P. Gärdenfors, and S. Wölfl, editors, *Spatial Cognition VI*, pages 361–377, Berlin Heidelberg, 2008. Springer.

[6] P. Kiefer and K. Stein. A framework for mobile intention recognition in spatially structured environments. In *2nd Workshop on Behavior Monitoring and Interpretation (BMI08)*, pages 28–41, 2008.

[7] M.-P. Kwan. Analysis of human spatial behavior in a gis environment: Recent developments and future prospects. *Journal of Geographical Systems*, 2(1):85–90, 2000.

[8] P. Laube, M. van Krefeld, and S. Imfeld. Finding remo - detecting relative motion patterns in geospatial lifelines. In *Developments in Spatial Data Handling, 11th Int. Symposium on Spatial Data Handling*, pages 201–215, 2004.

[9] B. Lenntorp. Paths in space-time environments: A time-geographic study of the movement possibilities of individuals. *Lund Studies in Geography, Series B*, 44, 1976.

[10] Q. Li, Y. Zheng, X. Xie, Y. Chen, W. Liu, and W.-Y. Ma. Mining user similarity based on location history. In *GIS '08: Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems*, pages 1–10, New York, NY, USA, 2008. ACM.

[11] L. Liao, D. J. Patterson, D. Fox, and H. Kautz. Learning and inferring transportation routines. *Artificial Intelligence*, 171(5-6):311–331, 2007.

[12] H. J. Miller. A measurement theory for time geography. *Geographical Analysis*, 37(1):17–45, 2005.

[13] D. V. Pynadath. *Probabilistic Grammars for Plan Recognition*. PhD thesis, The University of Michigan, 1999.

[14] M. Raubal, H. J. Miller, and S. Bridwell. User centered time geography for location-based services. *Geografiska Annaler B*, 86(4):245–265, 2004.

[15] M. Raubal, S. Winter, S. Teßmann, and C. Gaisbauer. Time geography for ad-hoc shared-ride trip planning in mobile geosensor networks. *ISPRS Journal of Photogrammetry and Remote Sensing*, 62(5):366–381, 2007.

[16] C. Schlieder. Representing the meaning of spatial behavior by spatially grounded intentional systems. In *GeoSpatial Semantics, 1st Int. Conference*, volume 3799 of *LNCS*, pages 30–44. Springer, 2005.

[17] G. Trajcevski, H. Ding, P. Scheuermann, R. Tamassia, and D. Vaccaro. Dynamics-aware similarity of moving objects trajectories. In *GIS '07: Proc. of 15th ACM International Symposium on Advances in GIS*, pages 1–8, New York, NY, USA, 2007. ACM.