Location-based decision support for user groups

Martin Espeter[a] and Martin Raubal[b]*

[a]*Institute for Geoinformatics, University of Münster, Münster, Germany;* [b]*Department of Geography, University of California, Santa Barbara, USA*

The ongoing progression of mobile communication devices, in particular with respect to positioning capabilities, has enabled the development of a new generation of location-based services (LBS). One of the most important aspects of current research on LBS is personalisation but it has been treated primarily for individual users. This article presents a first step towards personalised LBS that support user groups in their everyday decision-making, such as deciding where and when to meet for a common activity. The principles behind location-based group decision processes are outlined and a formal model for supporting such processes using methods of multi-criteria decision-making, time geography and similarity measurement is defined. This model is then implemented in the LBS prototype *mediatrix*. The prototype is used for simulating a location-based decision process aimed at finding an optimal restaurant for a user group in a city.

Keywords: location-based service; multi-criteria decision-making; time geography; similarity measurement; group decision-making

1. Introduction

The capabilities of mobile navigation and communication devices are rapidly improving. On the one hand, mobile routing services based on global positioning system (GPS) support people during wayfinding. On the other hand, the advent of mobile communication technologies such as general packet radio service (GPRS) and universal mobile telecommunications system (UMTS) has enabled users of mobile devices to access the internet anywhere at any time. The integration of both within single devices has led to the development of a new generation of location-based services (LBS). Knowing the position of the user, as well as the location of available information sources allows for increasing the benefits of mobile services dramatically.

Personalisation of services is a critical factor for improving the utility of LBS to help people in making good decisions in their mobile everyday lives (Raper *et al*. 2007a). Recent research activities have focussed on various aspects of personalisation, that is, the customisation and adaptation of LBS to their users. This trend to use highly specialised LBS has been intensified by people's increased need to acquire and use spatial and temporal information. In today's world of vast mobility and change we frequently face new situations in unfamiliar environments, such as finding

*Corresponding author. Email: raubal@geog.ucsb.edu

2   *M. Espeter and M. Raubal*

one's way in an unfamiliar city. So far, the focus of research on personalised LBS has
40 been targeted at individual users, their situational and personal context and with
regard to mobile map applications (Schmidt *et al.* 1999, Raubal and Panov 2009).
However, location-based decisions are not only made by individuals but also by
groups of users (Golledge and Stimson 1997), which requires some kind of mediation
process among them.
45   The objective of this article is to investigate group decision-making in a mobile
context and provide a framework for the implementation of LBS, which support
groups of people in their everyday decision-making based on spatio-temporal
constraints and user preferences. According to the list of significant LBS research
issues presented by Raper *et al.* (2007b) we do not strive for presenting *ad-hoc*
50 solutions for improving LBS but to give an insight into the possibilities for future
services arising from the combination of several areas of research, such as time
geography, multi-criteria decision analysis (MCDA) and similarity measurement.
Location-based decision services (LBDSs) (Rinner and Raubal 2004) serve as the
foundation for this work. This idea and related research to *personalised* LBS are
55 outlined in the following section. In addition, a brief summary of time geography
and human decision-making is given. In Section 3 we introduce our use case for
location-based group decisions, that is, choosing a restaurant in the city of Münster.
Section 4 defines the optimal decision outcome of location-based group decision-
making (LBGDM) according to the scenario. Based on this definition we define a
60 formal multi-criteria decision making (MCDM) model that allows for the calculation
and retrieval of such outcomes. In Section 5, the design and implementation of a
prototypical location-based group decision service realising the previously defined
MCDM model is described. This prototype is used for a simulation of a decision-
making process according to the given scenario. The simulation and an evaluation of
65 the results are given in Section 6. The final section presents conclusions and
directions for future research.

2. Related work

The presented research focusses on two aspects of personalising LBS for groups
of users: optimising location-based information retrieval using methods of multi-
70 criteria evaluation and integrating spatio-temporal constraints using principles of
time geography. This section portrays the theoretical background for the LBGDM
model developed here. We start with a brief overview of human decision-making,
introduce the concept of a LBDS, and describe the principles of time geography.

2.1. *Human decision-making*

75 There is still insufficient knowledge about how mobile location-based decision-
making is different from generic decision-making (Raper *et al.* 2007b). General
decision theory covers a wide range of models with different foci on describing how
decisions could or should be made, and on specifying decisions that are made
(Golledge and Stimson 1997, Amedeo *et al.* 2009). Human decision-making is not
80 strictly optimising in an economical and mathematical sense (Simon 1955), such as
proposed by the algorithms of classical decision-making theories, therefore

behavioural decision theory has been emphasised in the cognitive literature. In this article, we implement a criterion-based judgment approach but several others exist. A classification of decision-making models in terms of rationality is presented in Todd and Gigerenzer (2000). They distinguish between unbounded rationality, optimisation under constraints, satisfying, and their own approach of fast and frugal heuristics.

In order to investigate whether principles of generic decision-making can be transferred to mobile decision-making and find potential differences, researchers have developed tools to study the interaction between environments, individuals and mobile devices. Most case studies focus on pedestrian navigation in various settings, such as urban environments (Li and Longley 2006). Raubal *et al.* (2004) proposed a user-centred theory of LBS, which specifically focusses on individuals' mobile decision-making. It integrates spatial, temporal, social (using affordances) and cognitive (using decision-making theory) aspects of LBS.

2.2. *Location-based decision services*

LBDSs are tools for supporting everyday decision-making in a mobile context. These services are based on the integration of MCDA and can therefore provide analytic evaluations of the attractiveness of alternative destinations and choices being offered (Rinner 2008). MCDA methods had been introduced to geographic information systems in the 1990s for applications, such as site suitability analysis (Malczewski 1999). Rinner and Raubal (2004) designed a service called *Hotel Finder* by integrating the ordered weighted averaging (OWA) decision rule (Yager 1988). This software features multi-criteria decision support for the task of finding suitable hotels in an unfamiliar environment depending on the user's location and preferences. The usefulness of the *Hotel Finder* was demonstrated through a comprehensive user test showing that MCDM-based decision support can be employed for optimising location-based decision processes (Bäumer *et al.* 2007). The results confirmed that applying the multi-criteria decision strategy enhances people's decision support in unfamiliar environments. Until now, LBDS were restricted to single users and did not support groups of users in making location-based decisions. Research in the field of spatial decision support systems (SDSS) has shown that multi-criteria evaluation methods can also be applied to supporting group decision processes that depend on spatial information (Jankowski 1997). Such systems have been referred to as *collaborative SDSS* (Jankowski *et al.* 2006).

2.3. *Time geography*

An important aspect of personalised LBS is the integration of the users' spatio-temporal constraints. Recent work has shown that principles of time geography (Hägerstrand 1970) can be utilised to model spatio-temporal constraints in LBS (Raubal *et al.* 2004). Time geography defines the space-time mechanics of people and their environment by considering different constraints for people's ability to be present at a particular location in time – the capability, coupling and authority constraints (Hägerstrand 1970). The possibility of being present at a specific location and time is determined by people's ability to trade time for space, supported by
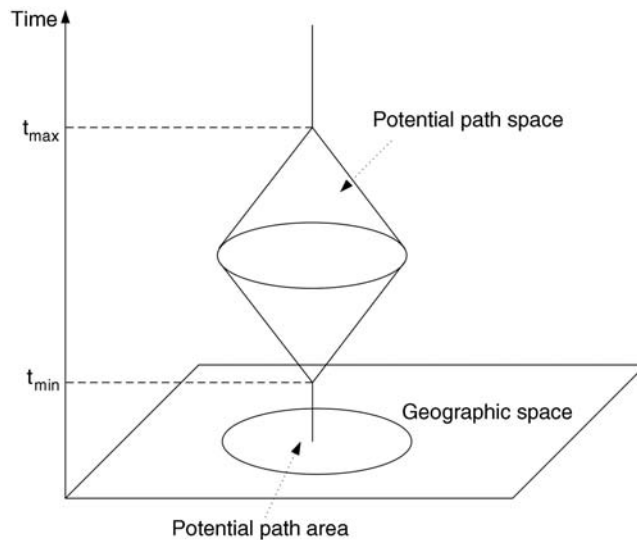
4   *M. Espeter and M. Raubal*

Figure 1. STP including PPS and PPA, according to Miller (1991b).

125   transportation and communication services. *Space–time paths* depict the movement
       of individuals in space over time. Such paths are available at various spatial (e.g.
       house, city, country) and temporal granularities (e.g. decade, year, day) and can be
       represented through different dimensions. All space–time paths must lie within
       space–time prisms (STPs) (Figure 1). These are geometrical constructs of two
130   intersecting cones and their boundaries limit the possible locations a path can take
       based on people's abilities to trade time for space. The inside of a STP is usually
       referred to as *potential path space* (PPS), the projection of STPs onto geographic
       space is called *potential path area* (PPA).
              The graph-related adaptation of the STPs described by Miller (1991a) can be
135   applied to compute network time prisms (NTPs) for mobile agents in an urban
       network. This was implemented (Raubal *et al.* 2007), realising a filtering technique
       for selecting feasible host–client combinations in a shared-ride trip planning scenario
       based on the intersection of *potential path trees* (PPT), which are the network
       equivalents to PPAs.

140   ## 3. Use case

       The possibility for location-based group decisions occurs, if there is a group of users
       whose STPs overlap for a specific time interval. To address such decision processes
       we introduce the notion of LBGDM. LBGDM can deal with a variety of different
       location-based tasks.[1] The core question is thereby the same: 'What is the best place
145   to perform a specific task?'
              LBGDM addresses all components of geographic information (Goodchild
       et al. 1999): *temporal*, *spatial* and *thematic* components. The selection of places for
       location-based tasks greatly depends on the local knowledge of the decision maker.
       This work focusses on cases of *ad-hoc* LBGDM in which the decision makers have

Table 1. User profiles for the task 'going out for dinner'.

Group member	Priority	Choice	Location	Time limit (destination)
Alice	Price	Chinese	Harbour	–
Bob	–	Mexican	University castle	8:30 pm (train station)
Charlie	Cuisine	Mexican	Hotel	8:15 pm (back to hotel)

150 little knowledge of their environment and there are only limited resources for a detailed investigation of the decision alternatives, for example, using a location-aware search engine, such as Google[TM]. The presented idea of LBGDM is based on the concept of friend-finder services, which visualise the location of contacts on a mobile map.[2] These services enable groups of users to spontaneously meet to

155 perform common tasks, such as having dinner. The selection of a meeting point, as well as a place for performing the task, for example, a restaurant, requires a group decision process. In the following, we introduce the scenario for LBGDM to be used for this work.

Alice is visiting the city of Münster (Germany) to attend a business meeting in the

160 area of the harbour. She has a free time slot in the evening and queries her friend-finder service to check whether any of her contacts are located in Münster. The friend-finder service shows her the position of two of her contacts: Bob and Charlie. Bob is currently attending a conference in the University castle and Charlie is in his hotel room. Alice sends a short message to both and invites them to go out for

165 dinner. She has little knowledge of the city and its places. Therefore, she suggests meeting at the train station and then discussing where to go. Each of the three persons has different constraints and preferences. These can be summarised as user profiles (Table 1). Alice likes Chinese food, but for her it is most important not to pay too much for dinner. Bob and Charlie like Mexican food. While Bob has no

170 particular priority, it is very important for Charlie to have Mexican food.

They meet at the train station at 7:00 pm. Now they have to find out which restaurants are nearby and meet their requirements. They start by querying the search engines on their mobile web browsers and then discuss the results that are retrieved. Alice has no more appointments this evening, but Bob has to catch a train

175 at 8:30 pm, and Charlie has to be back at the hotel in order to attend a conference call at 8:15 pm. Deciding where to go takes longer than expected, by this time there is only 1 h left until Charlie has to start back to his hotel. They decide to go to a nearby rather expensive Italian restaurant to save time for dinner. What they missed was that there are several nice restaurants close to Charlie's hotel, which they could have

180 easily reached if they had met there directly and not at the train station. Decision processes as described above can be time consuming and do not guarantee satisfying outcomes. In addition, such processes are always influenced by the discussion behaviour of the group. Each of the available options, for example, the restaurants in the case described above, vary in suitability with respect to the overall set of

185 constraints and preferences. The larger the gap between individual interests, the harder it is to find an overall satisfying solution. We argue here that such decision processes can be supported by methods of MCDM.

6　　　　　　　　　　　　　*M. Espeter and M. Raubal*

4. A formal model of LBGDM

Before defining a MCDM model for any kind of decision support the objectives of
the decision process must be identified. The objective of the location-based decision
described in the previous section is to find the optimal place to have dinner. We use
the notion of *optimal decision outcome* to address this objective of LBGDM.

4.1. *Optimal decision outcome*

The optimal outcome of location-based decisions as illustrated in this work is defined
as the place that (1) does not violate any individual constraint, (2) is the best match
of the individual preferences and (3) is not a disadvantage for any group member.
The definition of the optimal decision outcome places requirements upon the model
to be developed:

(1) It must allow decision makers to formulate *constraints*, in particular, spatio-
temporal constraints. Within MCDM constraints are sometimes considered
hard selection criterion (Rinner and Raubal 2004), in common language they
are often called *K.O. criteria*.

(2) It must provide quantitative methods for analysing decision alternatives with
respect to user preferences.

(3) It requires *mediation* functionality to ensure that no group member is
disadvantaged. If an alternative performs well for a majority of group
members but badly for a minority, it has to be considered less optimal than
an alternative that ensures that each group member is at least satisfied, even
if the performance is worse for the majority.

4.2. *Spatio-temporal screening*

In an area, such as the city of Münster the multitude of restaurants and bars provide
many alternatives for decision processes, such as illustrated earlier. The more
identifiable alternatives there are, the more complex the decision problem becomes.
The first step of the proposed analysis aims at screening those alternatives that are
not feasible with respect to *spatio-temporal* constraints. As mentioned in Section 2.3,
Hägerstrand (1970) identified three categories of spatio-temporal constraints:
capability, *coupling* and *authority constraints*. Capability constraints limit the activity
possibilities of an individual due to available resources. Depending on the mode of
transportation an individual can have different capability constraints. In our
scenario, capability constraints are defined by the walking speed of the individual
group members.[3] Coupling constraints limit the activity possibilities of an individual
by requiring the concurrent presence with other individuals at one place for a specific
time interval. In LBGDM, coupling constraints are set by the personal schedule, for
example, meetings or departure times, and the *stops* that allocate a task for a given
time in a specific place.[4] Authority constraints limit the accessibility of places for
specific time intervals. Restaurants, for example, impose authority constraints on
their guests through their opening hours.

To account for spatio-temporal constraints we adopt the network-based
algorithmic solution presented in Raubal *et al.* (2007). It optimises the selection of

230   shared rides in a transportation network depending on the clients and hosts' STPs. The underlying problems of determining the set of feasible hosts in shared-ride trip planning and determining the set of feasible alternatives in LBGDM are similar. In both cases an assessment whether a particular location, either a host's position or a place alternative, is reachable within a given time must be made. For LBGDM such

235   a filtering mechanism should yield those nodes of a street network for the area of interest at which feasible places are located. The particular method involves the computation of PPT conceptualised as the network equivalents of the *se (start, earliest)*-cone and the *dl (destination, latest)*-cone (Winter and Raubal 2006). The overlap of both trees results in a NTP (Wu and Miller 2001), the network equivalent

240   of the general STP. To adopt this approach for LBGDM the relevant *se*- and *dl*-cones must be identified. If a group decides to perform a location-based task, its members typically agree on a start time, for example, dinner at 7:00 pm. This article focusses on such cases, in which the individual group members are not co-present at one location, but spread across an urban area. For LBGDM the *se*-cone is defined as

245   the part of the space–time continuum that is reachable from the start point in space (and time) and the time difference from this start point and the beginning of the first task (Figure 2a). If the task starts at 7:00 pm and a group member can start travelling at 6:30 pm, the *se*-cone for this member is the sub-tree of the street network that is reachable within 30 min from the start node. The *dl*-cone for LBGDM has to be

250   considered if a group member has a particular destination she must reach by a given time after meeting with the group (Figure 2b). She might, for example, need to catch a train at 8:30 pm. Destinations in space and time are the basis for creating the *dl*-cone. The size of the *dl*-cone is determined by the time that goes by between the end
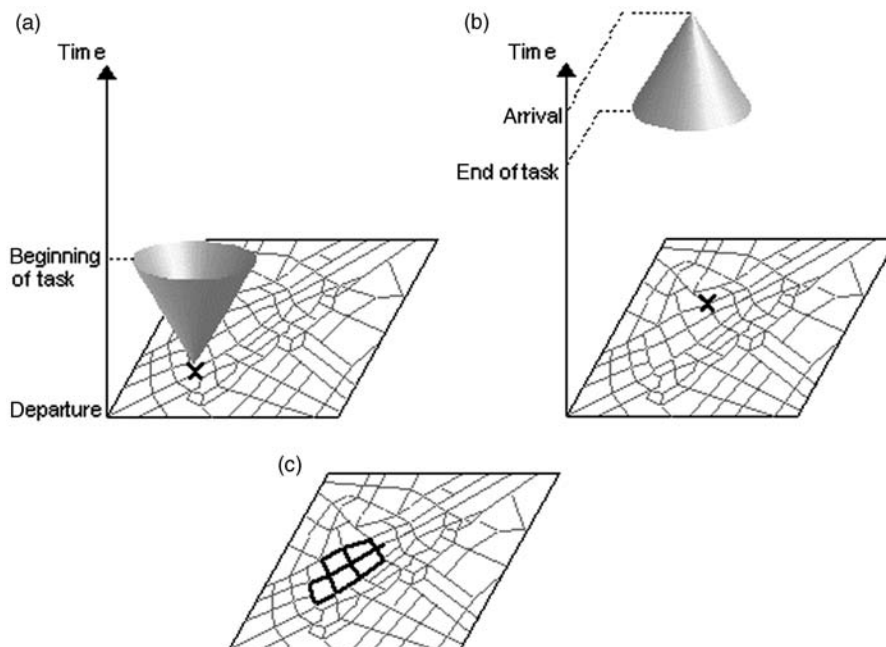

Figure 2. Spatio-temporal filtering: (a) *se*-cone, (b) *dl*-cone and (c) NTP.

255 time of the task and the time limit. If dinner ends at 8:00 pm there are 30 min left to get from the restaurant to the train station. With a sequence of tasks, the end of the final task must be considered for creating the *dl*-cone. The overlap of both cones leads to a NTP to be used for filtering the feasible places with respect to one group member's individual constraints. Overlapping the individual NTPs yields the feasible places with respect to the group's overall constraints (Figure 2c).

260
4.3. *Stop assessment*

After the set of feasible places has been determined the viability of each place with respect to the users' preferences and non-spatio-temporal constraints must be assessed. Besides dealing with constraints, such as price limits, this process also requires scores for the relevant decision criteria, based on *compensatory* MCDM
265 techniques. In the case of the task 'going out for dinner' the criteria may be prices, place ratings and cuisine. To fulfil the second definition of the optimal decision outcome for LBGDM it must be assessed how well each alternative performs with respect to the user preferences. This requires the use of a *decision rule*. Decision rules are compensatory procedures for ordering decision alternatives according to their
270 performance with respect to the objective (Malczewski 1999). In this case the objective is characterised by the definition of the optimal decision outcome. Compensatory MCDM techniques require *numerical* and *standardised* decision variables (Jankowski 1995). Depending on the scale of the criteria the application of such techniques requires transformations. Ratio scales, the scale of choice for
275 modelling price, generally are not standardised. The standardisation of ratio variables can be achieved by applying linear scale transformation. For this purpose we use the *score range procedure*, which ensures that the whole range between 0 and 1 is used. In the case of benefit criteria, such as place ratings, raw values are standardised by dividing the difference between the raw value and the minimum
280 value by the range (F 1). Since place ratings are modelled using ordinal scales, the raw values for applying formula 1 refer to the position (index) of a particular value within the given range. In the case of cost criteria, such as price limits this formula needs to be modified slightly (F 2).

$$(F1) \quad v_{norm} = \frac{v_{raw} - v_{min}}{v_{max} - v_{min}} \qquad (F2) \quad v_{norm} = \frac{v_{max} - v_{raw}}{v_{max} - v_{min}}$$

In both cases a value of 0 is given to the worst possible score, whereas a value of 1
285 is given to the best possible score. To account for the spatial distribution of alternatives, minimum and maximum values are taken from those alternatives within the NTP that is determined by the group's spatio-temporal constraints. The assessment of each variable is therefore relative to the other variables of the same type provided by the surrounding alternatives.
290 Integrating attributes on nominal scales, for example, cuisines into a compensatory MCDM approach is not straightforward. In general, nominal scales only provide information on whether two values are identical or not. We therefore propose the use of similarity measurement methods for integrating nominal data into a compensatory MCDM process. If people discuss where to go for dinner they often
295 decide about the cuisine that is offered by a place, for example, they like Chinese or

Mexican food. According to the first law of geography (Tobler 1970) 'everything is
related to everything else, but near things are more related than distant things'. This
can also be assumed for cuisines on a world-region scale. The Japanese and the
Chinese cuisines are more related than the Japanese and the Mexican cuisines. Such
300   relatedness can be derived by the common sense classification of world regions,[5]
which can be used to classify restaurants according to the region whose cuisine they
provide. The open directory project[6] uses a similar classification for structuring
recipes on their web portal. To quantify the relatedness of two cuisines, we utilise the
hierarchical structure provided by those classifications. Hierarchies can be modelled
305   as concept graphs consisting of nodes that are connected via *is-a* links (sub-concept
relations). The semantic distance between concepts in a hierarchy can be employed
to assess the semantic similarity of two concepts (Rada *et al*. 1989). Figure 3 shows
a graphical view of the cuisine hierarchy used in this model.

    This article presents an approach to measure the similarity between a cuisine
310   objective c_{obj} and a cuisine alternative c_{alt} based on the distance measure dist(c_{obj},
c_{alt}) between the nodes that allocate the cuisines in the hierarchy (F 3).

$$(F3) \quad sim(c_{obj}, c_{alt}) = \begin{cases} 1 & \text{if } c_{obj} \text{ subsumes } c_{alt} \\ 0 & \text{if } lub(c_{obj}, c_{alt}) = top \, . \\ 1/dist(c_{obj}, c_{alt}) + 1 & \text{else.} \end{cases}$$

If the cuisine alternative is subsumed by the cuisine objective (e.g. Chinese cuisine is
subsumed by Asian) the similarity value is 1. Hence, the proposed similarity measure
is asymmetric in the way that a super concept is considered equal to its sub concepts,
315   which is inverse to the way asymmetry is usually considered (Tversky 1977). The
proposed understanding of asymmetry is reasonable, since people may want to select
different levels of the hierarchy. If a person wants an Asian dinner she does not
bother whether the restaurant provides Chinese or Indian food. If the most specific
common super concept or least upper bound (*lub*) (Rodríguez and Egenhofer 2003)
320   of c_{obj} and c_{alt} is the top-concept, the similarity score is 0 (e.g. Chinese to German).
Similarity is a decaying function of distance, therefore the inverse distance is taken as
input for the decision analysis. This leads to a value range between 0 and 1, which is
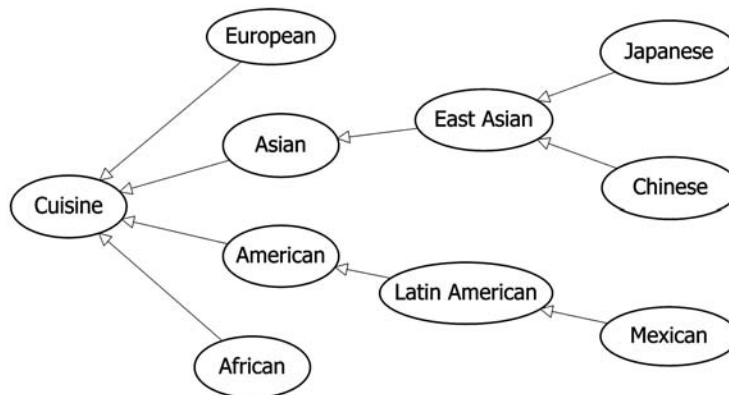

Figure 3. Taxonomy for measuring similarity between cuisines (subtree).

Table 2. Selected similarity scores.

Objective	Alternative	Similarity score
Chinese	Chinese	1
Chinese	East-Asian	0.67
Chinese	Japanese	0.5
Chinese	Indian	0.25
Chinese	German	0
Asian	Chinese	1

an implicit standardisation. Additionally, the distance is always incremented by 1 to ensure that a distance of 0 leads to a similarity value of 1. The resulting similarity values are strongly influenced by the weights that are assigned to the links of the hierarchy. We choose here a value of 0.5 to achieve reasonable results. Table 2 shows selected similarity scores for measuring similarity between cuisines.

After the relevant criteria scores have been computed, the decision alternatives can be assessed by considering the user preferences. We use the *point allocation weighting method*, which allows each group member to allocate 100 points to the set of decision criteria, that is, price, rating and cuisine. The scores combined with the individual weights are aggregated via the *simple additive weighting* (SAW) technique, an additive decision rule based on weighted arithmetic mean computation. SAW is sometimes called *scoring* or *weighted linear average* and is one of the most frequently used techniques for spatial multiple attribute decision-making. SAW scores each decision alternative *A* with respect to a user *j* by summing up the product of each criterion score C_i and the associated weight w_i for *m* relevant decision criteria (F4).

$$(F4) \quad A_j = \sum_{i=1}^{m} w_i C_i.$$

The input for SAW is typically specified via decision tables that store the criterion scores for each alternative. Applying SAW results in a ranked list of place alternatives for each user.

4.4. *Mediation*

To assess the performance of a stop for the whole group the individual stop scores have to be aggregated. One could simply use arithmetic means, as done by the SAW method. However, the application of arithmetic means for assessing group stops does not guarantee optimal decision outcomes. Arithmetic means can lead to a violation of the third requirement (Section 4.1), namely that no group member is disadvantaged. If one place provides high scores for two of the group members (e.g. 0.8 and 0.9) but a low score for a single one (e.g. 0.2), the arithmetic mean gives the relatively high value of 0.63. The result implies that this alternative performs well with respect to the group's interests. It conceals that the third group member may not be satisfied by this selection. If there is another alternative that achieves scores of 0.6 for each user, the arithmetic mean will be 0.6, which is lower than the score assigned to the first alternative. According to the definition of the optimal decision outcome, the latter alternative should be preferred. In other words, a *mediation* process
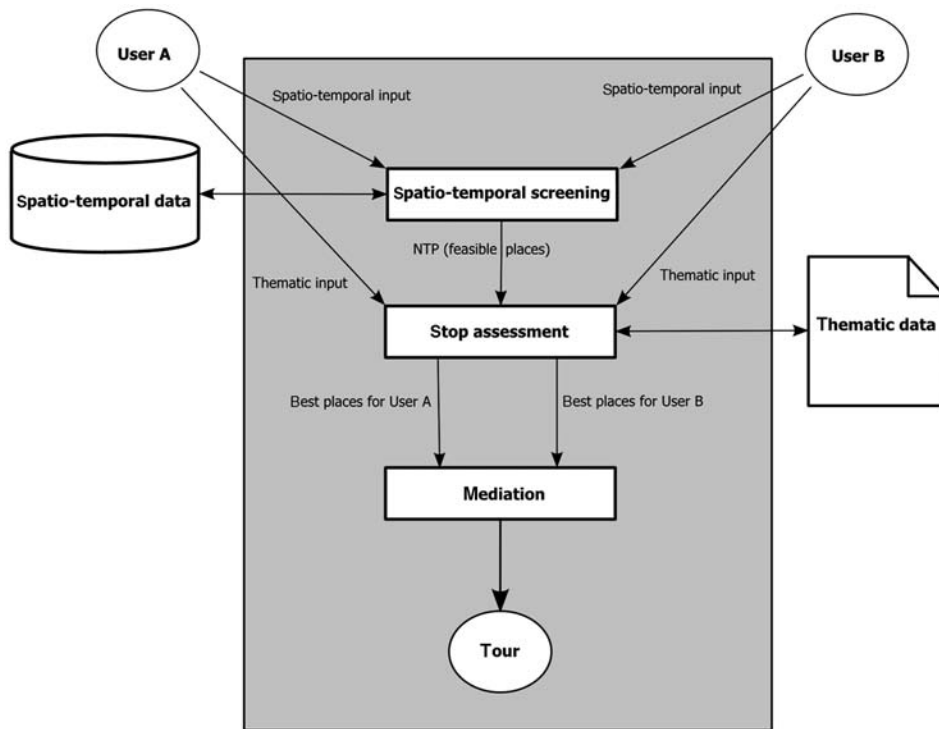
Figure 4. Overview of LBGDM model.

355   between user preferences is required. Therefore, we suggest another aggregation
technique for stop assessment of groups: the computation of *harmonic means* (Bullen
2003). The score of one stop S is the harmonic mean of all alternative scores A for
each of n users (F5).

$$(F5) \quad S = \frac{n}{\sum_{j=1}^{n} \frac{1}{A_j}}.$$

Using harmonic means leads to a larger impact of low scores on the result. In the
360   example mentioned above the harmonic mean of the first alternative is 0.48, whereas
the score of the second alternative is still 0.6.

After the mediation process has been performed the alternatives are ranked so
that the best alternative fulfils the requirements of the optimal decision outcome.
Taking it a step further, location-based group decision support service (LBGDS)
365   could also be designed to account for multiple tasks, for example, start with dinner
and continue with going to the movies or having some drinks. Single user decision
support for such task combinations was realised in the project *utopian*.[7] To keep the
possibility for supporting multiple tasks open, we refer to the result of the decision
process as a *tour*. A tour can comprise one or more stops that allocate particular
370   tasks to given places, as well as the paths the users have to follow to get to the stops
and their potential destinations.

Figure 4 summarises the methods presented in this section for the case of two
users and shows how they can be combined into a model that supports the retrieval

375   of the optimal decision outcome in a location-based group decision process as defined in Section 4.1.

5. Prototype

In the following, the presented model will be realised and evaluated in a prototypical LBGDS called *mediatrix*.[8]

The classic approach for developing LBS is to deploy the whole application on
380   the mobile device without requiring network access (*fat-client*). An example for a fat-client is the first version of the *Hotel Finder* (Raubal and Rinner 2004). This solution is suitable for simple problems involving a small data set, but not for LBS used to answer complex spatio-temporal queries. Recent developments of mobile devices, in particular with respect to their communication capabilities, have offered the
385   possibility to develop LBS that also involve server components to be accessed over a network. The latest version of the *Hotel Finder* (Bäumer *et al.* 2007) is an example of such distributed LBS. These systems still require the installation of service-specific client software on the mobile device. In the context of mobile applications this requirement is especially critical. The market for personal digital assistants (PDAs)
390   and Smartphones has become highly dynamic and is competitive with contenders offering ambitious platforms, such as the Apple[TM] iPhone, Google[TM] Android, Windows[TM] Mobile and Symbian[TM] (S60). Software providers have to adjust their applications to each platform they want to support, which can be a time consuming task. A novel approach for designing LBS is to utilise web browsers as client
395   components. This has recently gained importance in the Internet community and benefited from the evolution of web browser technology. One of the most important results was the creation of the *AJAX* – pattern (asynchronous javascript and XML) (Garrett 2005). AJAX describes the development of web applications unifying the benefits of classical web and desktop applications. They provide sophisticated
400   functionality and a dynamic user interface with only a web-browser on the client. At the core of AJAX is the *asynchronous XMLHTTPRequest* that allows reloading only specific parts of a web page instead of the whole page as done by classic web applications. Prominent examples for current AJAX-applications are Google Maps[TM] and Flickr[TM].

405   ### 5.1. *Client*

For the implementation of *mediatrix* we followed the AJAX-approach. The client is realised using hypertext markup language (HTML), cascading style sheets (CSS) and JavaScript. The server component is based on Java[TM] Servlet Technology and the Apache Wicket web application framework. The user interface is optimised for a
410   resolution of 240*320 pixels, which is the *de facto* standard for displays of current mobile communication devices. Apache Wicket has been extended by some AJAX-enabled components, such as drop-down choices and links that allow reacting to user input by dynamically reloading other page components. This allows the development of a dynamic web front-end with the look-and-feel of a fat-client. To access *mediatrix*
415   the user must visit the homepage and log in. After the log-in, the user gets to the

index page, where she can create a tour request, join an existing tour request, edit her profile or view computed tour proposals.

420 One of the advantages of using current AJAX applications is the possibility to combine various online data sources to one hybrid application, called *mash-ups* (Scharl 2007). Google Maps^TM has proven useful for *mash-ups* that require the visualisation of geographic information. For *mediatrix* the localisation of the users, their destinations and the visualisation of the computed tour have been realised this way. The client component has been tested on a PDA equipped with Mozilla Minimo which is a mobile browser that supports AJAX-based web applications.

425 5.2. *Data*

LBGDS require several types of data: network data, user data, place data and request data. The network data are provided by TeleAtlas® and stored in a relational database (RDB) consisting of node and edge tables. User profiles and their inputs are mapped onto a RDB schema and also stored in a RDB. The RDB further stores 430 the place data, which consists of spatio-temporal and thematic data. The thematic data include information on different scales. Ratio and ordinal data (e.g. prices and ratings) are stored using standard structured query language (SQL) data types. These are not sufficient to store the nominal data required for the decision analysis. Section 4.3 demonstrated how nominal data can be standardised using similarity 435 measurement. This requires data that is structured hierarchically. For this purpose, the cuisine data is stored in the RDB, but also linked to a cuisine hierarchy that is defined using resource description framework-schema (RDFS). RDFS extends resource description framework (RDF) by a standard vocabulary and some core semantics. In particular, it provides the possibility to model hierarchies that are 440 required for similarity measurement.

The current version of *mediatrix* supports group decision processes for up to three users with respect to the task of going out for dinner. The prototype accounts for spatio-temporal and price constraints, as well as for the opening hours of places. The integration of further data for planning tasks, such as going to the movies or 445 having a drink, and the possibility to combine tasks is left for future work. The user interface has been designed to select more than one task.

6. Evaluation

This section discusses the model and prototype that have been presented in the previous sections. It includes a simulation of *mediatrix* with respect to the scenario 450 described in Section 3. The results of this simulation are evaluated and used to assess whether the proposed model is able to achieve optimal decision outcomes.

6.1. *Simulation*

The scenario underlying this work presents an example for a group decision problem in which a group of three people with limited spatio-temporal resources tries to find 455 a restaurant in the city of Münster. The group is characterised by three user profiles (Table 2). These profiles are now taken as user inputs for running a decision process supported by *mediatrix*. According to the scenario, Alice starts the group task.

14   *M. Espeter and M. Raubal*

Figure 5. Create tour.

She wants to invite two of her friends, Bob and Charlie, to have dinner at 7:00 pm. Therefore, she logs on to *mediatrix* and creates a tour request with the required
460   parameters start time, invited users and task type (Figure 5).

After the request is registered by the service, it gets published to the invited users. At the current state of the prototype the users have to log in to check for tours they are invited to. For future versions it would be reasonable to integrate a notification service, for example, a short message service (SMS), which directly contacts users
465   after they have been invited to a tour. To join a tour request the invited users can select the tour name and view its details. They can either join the tour or decline the invitation. Figure 6 shows how Bob reacts to the invitation by Alice.

After joining a tour request the user must submit her personal input to the service, that is, the relevant constraints and preferences (Figure 7). Figure 8 shows
470   the Google Maps[TM] *mash-up* that is used for setting the start and destination. The input for a tour request is enriched by the personal user profiles that store static and request-independent data, such as weights (Figure 9). The profiles are loaded from the RDB. To perform the decision analysis, each user must submit her constraints and preferences.[9] Table 3 summarises the concrete user inputs for the tour request
475   created by Alice.

After the group's input is complete it is analysed with respect to the area of interest. According to Section 4.2, the analysis starts with spatio-temporal screening resulting in a group NTP that contains the set of feasible places. Table 4 lists the feasible places for the given request and the place data that is important for
480   the decision analysis. To assess the price level of restaurants, the minimum and the

Figure 6. Join tour.

Figure 7. Set input.

Figure 8. Set spatial input.

maximum price for a single dish are taken to calculate an average price. This is a simple, but plausible approximation of the price level which could be extended by taking all offers provided by a place into account.

Next, the relevant decision criteria are scored including normalisation and
485 similarity measurement. In this case the similarity measurement affects the cuisines provided by the feasible places and the choices made by each group member. The raw values have to be normalised and then aggregated with respect to the user weights using the SAW method. The results are shown in Table 5.

Finally, the place scores are aggregated to stop scores including the input of
490 the whole group. The decision strategy proposed here utilises harmonic mean computations for this step (Section 4.4). Table 6 shows the stop scores computed with harmonic mean compared to the geometric mean computation. The Enchilada achieves the highest score using arithmetic mean, whereas the Ipanema scores best with respect to the harmonic mean. China Corner and Altes Gasthaus Leve achieve
495 a score of 0 using harmonic mean. The resulting tour is shown in Figure 10.

6.2. *Results*

The results of the simulation are now analysed in the context of the definition of the optimal decision outcome. The optimal decision outcome of location-based group

Figure 9. Edit profile.

Table 3. User profiles for the task 'having dinner'.

User	Choice	Price weight	Rating weight	Choice weight
Alice	Chinese	80	10	10
Bob	Mexican	30	30	40
Charlie	Mexican	0	0	100

Table 4. Feasible places and their attributes.

Name	Cuisine	Rating	Min price (€)	Max price (€)
Altes Gasthaus Leve	German	4.38	8	22
China Corner	Chinese	4.75	3.50	8
Enchilada	Mexican	3.75	8.90	15.30
Ipanema	Latin American	2.5[a]	4.5	12

Note: [a]No rating available on www.restaurant-kritik.de (2.5 is the default rating).

decisions is defined in Section 4.1 as the outcome that does not violate any individual constraints and matches the preferences best without causing disadvantage to any group member. The first requirement, no violation of user constraints, is achieved by each feasible place. In order to confirm the second requirement the place scores have

18   *M. Espeter and M. Raubal*

Table 5. Aggregated place scores for each user.

Place	Alice	Bob	Charlie
Altes Gasthaus Leve	0.08	0.27	0
China Corner	1	0.59	0
Enchilada	0.33	0.72	1
Ipanema	0.63	0.64	0.67

Table 6. Aggregated stop scores.

Place	Score (arithmetic)	Score (harmonic)
Ipanema	0.65	0.65
Enchilada	0.68	0.55
China Corner	0.52	0
Altes Gasthaus Leve	0.11	0

to be considered. Due to its Mexican cuisine the Enchilada achieves high scores for
Bob and Charlie but because of the high price level a low score for Alice. Taking the
arithmetic mean for aggregating the user-specific place scores, the Enchilada achieves
the highest score and accordingly fulfils the second requirement. However, Alice
would not be happy with this solution and therefore the Enchilada violates the third
requirement. Using harmonic mean computation yields the Ipanema as the best
result. Since the Ipanema is less expensive, Alice can be quite satisfied with having
dinner there. For Charlie it is very important to have Mexican food. The Ipanema
provides Latin American cuisine, which is not the same but similar. For Bob both
places provide rather satisfying results. Taking everything into account it can be
concluded that the Ipanema is the best compromise that could be achieved for the
given decision problem and is therefore considered as the optimal decision outcome.
It follows that the proposed MCDM model allows for finding optimal decision
outcomes for location-based group decision processes.

6.3. *Discussion*

Several challenges remain for realising LBGDS according to the model presented.
First, one must investigate how closely human decision-making behaviour in
scenarios as described in this work can be approximated by the proposed model. This
requires a user-centred focus to investigate particular needs of the user, how they
interact with other users in a group, and how they make judgments and trade these
off. Such research has a long tradition and has been applied within the area of LBS
with a focus on individual users and user groups (Wealands *et al.* 2007, Raubal 2009)
for different scenarios, such as mobile guides (Baus *et al.* 2005). In particular and
regarding the work presented here, this affects the definition of the optimal decision
outcome, which has not yet been verified with respect to human judgements. The
identified decision criteria require further investigation. According to Malczewski
(1999), a set of MCDM criteria has to be comprehensive, measurable, complete,
operational, decomposable, non-redundant and minimal. Verification that these

Figure 10. Final result for dinner tour.

characteristics are provided by the set of MCDM criteria utilised in this work has
not yet been achieved. We must also assume that some additional criteria, such as
ambiance or place size, may play important roles for location-based decisions.

The dynamic aspects of LBGDS need further investigation, as well. Currently,
535   constant travel velocity is assumed and transportation networks, such as for buses
have not been regarded yet. Positioning via self-localisation in the current version of
mediatrix should be replaced by automated positioning techniques and geocoding
services. Finally, it has to be stated that our approach does not strive for guaranteed
perfect results, that is, very high scores for each user in general. The outcome of
540   location-based decision processes can rarely be perfect, because user interests vary
and the set of alternatives is strongly restricted by the spatio-temporal context.
Hence, the underlying notion of *optimal* should rather be understood in terms of *best
possible*. One of the core advantages of *mediatrix* is that it only requires *asynchronous
telepresence* of group members (Harvey and Macnab 2000). There is no need for
545   direct interaction as in a standard discussion process since the service maintains
requests that have been created until all users have submitted their input.

7. Conclusions and future work

This article presented a formal model and prototypical implementation for LBGDM.
It provides a foundation for the future development of personalised LBS that

20   *M. Espeter and M. Raubal*

550   support groups of users in their everyday planning of shared activities. Such
       applications include any location search for common activities, collaborative
       emergency response operations, mobile guides and the broad range of social
       network functions. We outlined examples and basic principles of personalisation in
       LBS, and presented a use case for LBGDM dealing with a group of people searching
555   for a restaurant in the city of Münster. A definition of the optimal decision outcome
       for LBGDM was given. The formal MCDM model aimed at obtaining such
       outcomes depending on personal constraints and preferences. Principles of time
       geography were used to develop a screening method that accounts for spatio-
       temporal constraints. Similarity measurement methods were employed to integrate
560   nominal decision criteria into decision rules. We proposed using harmonic means
       to avoid individual group members being disadvantaged. By simulating a decision
       process using the prototypical LBGDS *mediatrix* we demonstrated that the proposed
       model can be employed to achieve optimal decision outcomes for location-based
       group decisions.

565   There are several areas for future research with regard to improving the model
       presented in this work: spatio-temporal attributes have been considered as non-
       compensatory so far. Allowing compensatory spatio-temporal attributes would
       enable users to express preferences with respect to spatial-temporal criteria, for
       example, some users may prefer short travel distances. The proposed MCDM model
570   utilises a series of simple techniques. More sophisticated methods are available, for
       example, the OWA method. OWA allows for selecting between different personal
       decision strategies and has already been implemented in LBDS for single users
       (Rinner and Raubal 2004). Using OWA the user can select optimistic, pessimistic
       and moderate decision strategies. An optimistic strategy puts higher weights on
575   criteria with high scores, whereas a pessimistic strategy puts higher weights on
       criteria with low scores. Another MCDM technique that could be utilised for
       LBGDM is *sensitivity analysis* (SA) (Malczewski 1999, Ligmann-Zielinska and
       Jankowski 2008). Using SA in a LBGDS could provide helpful feedback for decision
       makers by showing how sensitive the selected criteria are with respect to changes in
580   user input. It could be combined with a voting mechanism offering several well-
       performing tour alternatives. For both MCDM techniques, OWA and SA, the
       high cognitive workload demanded from the user seems to be a major obstacle for
       employing them for location-based group decision support. As described in Section
       6.3, a user-centred focus will bring more insight to these questions.

585   The similarity measure proposed here has not been evaluated with respect to its
       correspondence to human similarity judgements. Considering the semantic distance
       method employed for measuring cuisine similarity it may be reasonable to include
       further similarity measures, for example, to exploit information contents as proposed
       by Resnik (1995). Resnik suggests using probabilities of encountering an instance of
590   a concept for measuring similarity in taxonomies. He defines information content as
       the negative logarithm of this probability. The similarity between two concepts C_1
       and C_2 is measured using the information content of the most specific class, or least
       upper bound, subsuming C_1 and C_2. For the top-class of the taxonomy the
       probability of encountering an instance is 1, which leads to a similarity measure of 0.
595   This is the result of comparing two concepts located in different main-branches of
       the taxonomy, for example, Chinese to German cuisine. The probability computa-
       tion depends on empirical, instance-based information. In the case of measuring

cuisine similarity, this translates to restaurant data. If there were many East-Asian restaurants (40% probability) and few African restaurants (5% probability) there would be a higher similarity between African restaurants, for example, sim (Tunesian, Egyptian), than between East-Asian restaurants, for example, sim (Japanese, Chinese), which seems plausible. A combination of the approach used in this work and the information content may improve the decision analysis.

Our major objective was to define a formal, computational model for enabling location-based decision support for user groups. This strongly influenced the development of the prototype, which was developed to demonstrate and analyse this model. As a next step, an evaluation of how such a service could be embedded in the service-oriented architecture provided by the Open-LS specifications[10] is necessary. *Mediatrix* has been designed and implemented as a stand-alone web application in the Web 2.0 style and does not provide interfaces to connect to other services. Aligning *mediatrix* to the Open-LS specification would allow accessing other services, such as geocoding and navigation services, which are appropriate extensions for a LBGDS.

Acknowledgements

Notes

1. We define location-based tasks as activities that are bound by space and time. For example, *eating* is an activity, whereas *having dinner* is a task.
2. For example, http://www.google.com/latitude, www.qiro.de, www.kakiloc.com
3. For reasons of simplicity a constant travel velocity (5 km/h) is assumed for each group member.
4. We assume a standard duration of 1 h for the task of having dinner.
5. http://unstats.un.org/unsd/methods/m49/m49.htm
6. http://dmoz.org/Home/Cooking/World_Cuisines
7. http://www.youtube.com/watch?v=m0zD_n3zEYk
8. *mediatrix* (Latin): female troubleshooter.
9. This simulation focusses on quantitative methods. Thus, no additional constraints, such as price limits are set.
10. http://www.opengeospatial.org/standards/ols

References

Amedeo, D., Golledge, R., and Stimson, R., 2009. *Person environment behavior research: investigating activities and experiences in spaces and environments*. New York: Guilford Press.

Bäumer, B., Panov, I., and Raubal, M., 2007. Decision improvement through multi-criteria strategies in mobile location-based services, *In*: A. Car, G. Griesebner and J. Strobl, eds. *Geospatial crossroads @ GI_Forum: proceedings of the first geoinformatics forum Salzburg*. Heidelberg: Wichmann, 17–25.

1

22   *M. Espeter and M. Raubal*

640 Baus, J., Cheverst, K., and Kray, C., 2005. A survey of map-based mobile guides, *In*: L. Meng, A. Zipf and T. Reichenbacher, eds. *Map-based mobile services*. Berlin: Springer, 197–216.

Bullen, P., 2003. *Handbook of means and their inequalities*. Boston, MA: Kluwer.

Garrett, J., 2005. Ajax: a new approach to web applications. *Adaptive Path*. [online]. Available
645 from: http://www.adaptivepath.com/ideas/essays/archives/000385.php

Golledge, R. and Stimson, R., 1997. *Spatial behavior: a geographic perspective*. New York: Guilford Press.

Goodchild, M., *et al.*, 1999. Introduction to the Varenius project. *International Journal of Geographical Information Science*, 13, 731–745.

650 Hägerstrand, T., 1970. What about people in regional science?. *Papers of the Regional Science Association*, 24, 7–21.

Harvey, A. and Macnab, P., 2000. Who's up? Global interpersonal accessibility, *In*: D. Janelle and D. Hodge, eds. *Information, place and cyberspace: issues in accessibility*. Berlin: Springer, 147–170.

655 Jankowski, P., 1995. Integrating geographical information systems and multiple criteria decision-making methods. *International Journal of Geographical Information Systems*, 9, 251–273.

Jankowski, P., 1997. Spatial group choice: a SDSS tool for collaborative spatial decision making. *International Journal of Geographical Information Science*, 11, 577–602.

660 Jankowski, P., *et al.*, 2006. Design considerations and evaluation of a collaborative, spatio-temporal decision support system. *Transactions in GIS*, 10, 335–354.

Li, C. and Longley, P., 2006. A test environment for location-based services applications. *Transactions in GIS*, 10, 43–61.

Ligmann-Zielinska, A. and Jankowski, P., 2008. A framework for sensitivity analysis in spatial
665 multiple criteria evaluation. *In*: T. Cova, H. Miller, K. Beard, A. Frank, & M. Goodchild, eds. *Geographic information science, 5th International conference, GIScience 2008*, September 2008, Park City, UT, USA. Berlin: Springer, 217–233.

Malczewski, J., 1999. *GIS and multicriteria decision analysis*. New York: John Wiley.

Miller, H., 1991a. Modeling accessibility using space-time prism concepts within geographical
670 information systems. *International Journal of Geographical Information Systems*, 5, 287–301.

Miller, H.J., 1991b. Modelling accessibility using space-time prism concepts within geographical information systems. *International Journal on Geographical Information Science*, 5, 287–301.

675 Rada, R., *et al.*, 1989. Development and application of a metric on semantic nets. *IEEE Transactions on Systems, Man and Cybernetics*, 19, 17–30.

Raper, J., *et al.*, 2007a. Applications of location-based services: a selected review. *Journal of Location Based Services*, 1, 89–111.

Raper, J., *et al.*, 2007b. A critical evaluation of location based services and their potential.
680 *Journal of Location Based Services*, 1, 5–45.

Raubal, M., 2009. Cognitive engineering for geographic information science. *Geography Compass*, 3, 1087–1104.

Raubal, M., *et al.*, 2007. Time geography for *ad-hoc* shared-ride trip planning in mobile geosensor networks. *ISPRS Journal of Photogrammetry and Remote Sensing*, 62,
685 366–381.

Raubal, M., Miller, H., and Bridwell, S., 2004. User-centred time geography for location-based services. *Geografiska Annaler B*, 86, 245–265.

Raubal, M. and Panov, I., 2009. A formal model for mobile map adaptation, *In*: G. Gartner and K. Rehrl, eds. *Location based services and telecartography II – from sensor fusion
690 to context models. Selected papers from the 5th international symposium on LBS & TeleCartography* 2008, Salzburg, Austria. Berlin: Springer, 11–34.

Raubal, M. and Rinner, C., 2004. Multi-criteria decision analysis for location based services. *In*: S.A. Brandt, ed. *Geoinformatics 2004, 12th International conference on geoinformatics*, 7–9 June 2004, Gävle, Sweden. Gävle: University Press, 47–53.

695   Resnik, P., 1995. Using information content to evaluate semantic similarity in a taxonomy. *Proceedings of the 14th international joint conference on artificial intelligence*. Montreal, Canada, 448–453.

Rinner, C., 2008. Mobile maps and more – extending location-based services with multi-criteria decision analysis, *In*: L. Meng, A. Zipfand and S. Winter, eds. *Map-based mobile*

700   *services*. Berlin: Springer, 335–352.

Rinner, C. and Raubal, M., 2004. Personalized multi-criteria decision strategies in location-based decision support. *Journal of Geographic Information Sciences*, 10, 149–156.

Rodríguez, A. and Egenhofer, M., 2003. Determining semantic similarity among entity Classes from different ontologies. *IEEE Transactions on Knowledge and Data*

705   *Engineering*, 15, 442–456.

Scharl, A., 2007. Towards the geospatial web: Media platforms for managing geotagged knowledge repositories, *In*: A. Scharl and K. Tochtermann, eds. *The geospatial web*. London: Springer, 3–14.

Schmidt, A., Beigl, M., and Gellersen, H., 1999. There is more to context than location.

710   *Computers and Graphics*, 23, 893–901.

Simon, H., 1955. A behavioral model of rational choice. *Quarterly Journal of Economics*, 69, 99–118.

Tobler, W., 1970. A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234–240.

715   Todd, P. and Gigerenzer, G., 2000. Précis of *simple heuristics that make us smart*. *Behavioral and Brain Sciences*, 23, 727–780.

Tversky, A., 1977. Features of similarity. *Psychological Review*, 84, 327–352.

Wealands, K., *et al.*, 2007. User assessment as input for useful geospatial representations within mobile location-based services. *Transactions in GIS*, 11, 283–309.

720   Winter, S. and Raubal, M., 2006. Time geography for ad-hoc shared-ride trip planning. *In*: K. Aberer, T. Hara and A. Joshi, eds. *7th International conference on mobile data management (MDM'06)*. Nara, Japan: IEEE.

Wu, Y.-H. and Miller, H., 2001. Computational tools for measuring space-time accessibility within dynamic flow transportation networks. *Journal of Transportation and Statistics*,

725   4, 1–14.

Yager, R., 1988. On ordered weighted averaging aggregation operators in multi-criteria decision making. *IEEE Transactions on Systems, Man and Cybernetics*, 18, 183–190.

3

4