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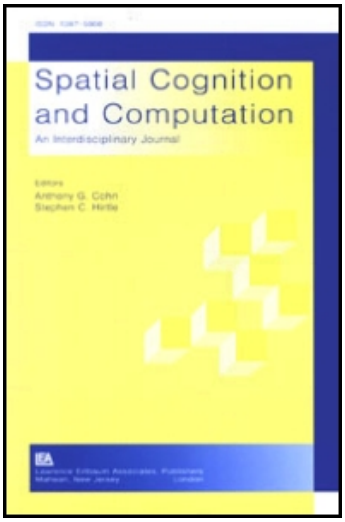


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# Generation of Adaptive Route Descriptions in Urban Environments

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# Generation of Adaptive Route Descriptions in Urban Environments

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**Abstract:** This paper addresses the automatic generation of adaptive and cognitively adequate verbal route descriptions. Current automatic route descriptions suffer from a lack of adaptivity to the principles people employ in wayfinding communication, as well as to particular users' information needs. We enhance adaptivity and cognitive adequacy by supplementing verbal route descriptions with salient geographic features, applying natural language generation techniques for linguistic realization. We also take users' familiarity with an area into account. We present an architecture for navigational assistance operating on human cognitive and linguistic principles and report an evaluative user study that confirms the usefulness of our approach.

**Keywords:** route descriptions, natural language generation, salience, granularity

## 1. INTRODUCTION

Adaptive route instructions aim to enhance the cognitive adequacy of automatically generated route instructions by implementing strategies that resemble the strategies that people use in their communication of routes. This means, cognitive adequacy is understood here in the sense of conforming to recognized cognitive and linguistic observations (for a discussion of the variety of meanings of cognitive adequacy see (Strube, 1992)). In this paper adaptivity is realized along the following dimensions: (a) the cognitive principles underlying human route descriptions, (b) the salient geographical features of the environment, (c) the user's prior knowledge of the environment, and (d) the language used by humans to convey navigation information. The first aspect is related to what (Lovelace, Hegarty, & Montello, 1999) have stated as characteristics of good route descriptions based on experimental findings

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involving human descriptions. We will especially focus on the following subset of these characteristics:

- providing the user with **preview information** on upcoming choice points
- including **landmarks** at choice points
- providing **confirmatory information** along the route to assure the user that they are still on the right track
- preferring the mention of landmarks over streets
- presenting information in a **sequential** fashion
- limiting the amount of extra information to a necessary minimum

The second aspect of adaptation is based on the assumption that route descriptions should refer to salient features of the environment, such as streets or landmarks, in order to maximize the helpfulness of the instructions. We apply appropriately adapted ranking mechanisms to streets and landmarks in order to determine their salience. The decision on what information to include in a description depends on the salience scores of geographical features as well as the level of granularity chosen for the route description. The level of granularity is related to the third aspect of adaptation, the user's prior knowledge of the area of navigation. We assume that users familiar with the environment will be able to find their way with a limited amount of detail and perceive too much redundancy as disturbing or patronizing. Unfamiliar users, on the other hand, have higher information needs. We provide turn-by-turn descriptions (Richter, 2008) for unfamiliar, and destination descriptions (Jiang & Liu, 2009; Tomko & Winter, 2009) for familiar users. Finally, the fourth aspect is addressed by applying natural language generation techniques that help us align our chosen verbalizations with a corpus of human route descriptions, introducing controlled variability in linguistic expressions.

Our contribution in this paper consists, first, of the integration of the aforementioned adaptive features into a system for navigational assistance, and, second, in an experimental evaluation of that system. Our user study tested the hypothesis that our generated descriptions will be indistinguishable from human descriptions and will be judged as considerably more helpful than web-based descriptions. This hypothesis was confirmed by the empirical evidence: ratings of our descriptions were close to those of human descriptions for turn-by-turn descriptions and better than those of human descriptions for destination descriptions. The hypothesis is designed in a way similar to the Spatial Turing Test (Winter, 2009). The assumption is that if users are not able to identify our instructions as computer-generated, then we achieve a level of naturalness that is comparable to that of human instructions.

The paper is organized as follows. We will first give an overview of related research and relate it to our own work. Subsequently, we will describe the contribution and approach of this paper. Next, we describe the adapted ranking mechanisms of geographical features. This is followed by a presentation of our mechanisms of realizing route descriptions at different

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levels of granularity, and a prototype implementation thereof. This prototype will be evaluated in the next section. Finally, we will draw conclusions and mention possible future work.

## 2. PREVIOUS WORK

Properties of human route descriptions have been studied in cognitive science and cognitive linguistics for a long time, at least going back to (Klein, 1979). This revealed certain central characteristics of human approaches to wayfinding tasks, including the principles of good route descriptions stated by (Lovelace et al., 1999) or the identification of a common skeleton underlying route descriptions presented by (Denis, 1997). He compared several descriptions of the same route and identified a common skeleton of a route description, which can be supplemented with additional information whenever there is need. This would suggest that conciseness is favored over highly redundant descriptions (Daniel & Denis, 2004). For the approach we present we considered both the work of Lovelace et al. (as stated in the introduction) as well as the work of Denis. The latter is integrated by the different types of instructions we distinguish based on cues of context (salience measures of present landmarks or traveled streets) and cues of the user (degree of familiarity). In this way, we achieve generation of different classes of descriptions, such as "actions with reference to a landmark," or "actions without reference to a landmark," some of which were shared by Denis. Our work takes into account findings that people rarely refer to distance in route descriptions, but prefer to use landmarks when identifying decision points (Michon & Denis, 2001; Denis, Michon, & Tom, 2007).

The term "landmark" existed in the wayfinding literature for a long time without a formal definition, e.g., (Lynch, 1960; Presson & Montello, 1988). What constitutes a landmark was then addressed by (Sorrows & Hirtle, 1999), and used for first algorithms for the identification of landmarks in geographic data sets (Raubal & Winter, 2002; Elias, 2003; Tezuka & Tanaka, 2005). According to this literature, landmarks are features of cognitive salience that stand out from other features in the environment. This also means that landmarks can be described by a measure of salience, and have a ranking, or be organized in a hierarchy based on their salience (Couclelis, Golledge, Gale, & Tobler, 1987; Winter, Tomko, Elias, & Sester, 2008). References to landmarks (e.g., churches, shops, traffic lights) can frequently be found in human route descriptions and play an important role in navigation tasks (Lynch, 1960; Lovelace et al., 1999; May, Ross, & Bayer, 2003). Streets can differ in salience as well (Tomko, Winter, & Claramunt, 2008), and are used together with, or in alternative to, landmarks in route directions (Tom & Denis, 2004).

Route descriptions can be classified into two categories. Turn-by-turn descriptions describe turn by turn *how* to find a destination. They are suited for

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in-situ descriptions, and are provided by web-based route planning services and car navigation systems. Turn-by-turn descriptions have been enriched in several ways, for example, by including landmarks at decision points or by chunking repeated actions or landmarks along the route (Klippel, Tappe, & Habel, 2003; Richter, 2008; Klippel, Hansen, Richter, & Winter, 2009). An alternative type of route descriptions are destination descriptions. They describe *where* a destination is, assuming that the recipient has sufficient knowledge to find this destination. (Tomko & Winter, 2009) have suggested an algorithm to generate destination descriptions, which are hierarchically structured and 'zoom-in' from more to less salient features.

Furthermore, combinations of turn-by-turn descriptions (for unknown parts of a route) and destination descriptions (for parts that lead through known environments) were suggested (Richter, Tomko, & Winter, 2008). This paper applies these formal models in combination with language generation in order to provide both types of descriptions and make an informed decision on the most appropriate form given the current context and user. Thereby we move a step further towards more flexible navigational user interfaces.

A further factor that can impact on the comprehensibility of route descriptions is their form of verbalization. Dale et al.'s CORAL system (Dale, Geldof, & Prost, 2005) employed natural language generation techniques to generate routes. They first divided the skeletal route (consisting of low-level instructions such as "straight," or "left") into high-level chunks by, for example, collapsing several consecutive instructions of the same type into one (e.g., several instances of "straight"). Second, they used aggregation which is a process to construct sentences that communicate several pieces of information at once. We follow Dale et al. in using natural language generation techniques for route realization, but go one step further by orienting our linguistic surface forms directly on human linguistic behavior as observed in a corpus of human-authored route descriptions. This has the advantage of making sure instructions are comprehensible and natural. Also, we provide an evaluation of our approach, whose scope goes beyond the rather small-scale evaluation of Dale et al.

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## 3. CONTRIBUTION AND APPROACH

Adaptive route description generation should be able to react flexibly to changing environmental features and conditions of use. However, to date no system exists that is able to adapt its output to contextual cues of the environment, such as the presence or absence of salient landmarks, or the salience of streets. Further, the information needs of individual users who may differ in their prior knowledge are not taken into consideration. Finally, state-of-the-art systems do not adapt their linguistic output to the language that humans use to convey route instructions, but instead employ rigid templates. All of these points are crucial however for the assistance of human wayfinding,

which is why this paper presents an important and novel contribution in several respects. First, we achieve a synergy of research on spatial salience models and natural language generation to contribute in a joint fashion to the cognitive adequacy of the resulting instructions. Second, aligning the linguistic properties of our descriptions to those of human-authored descriptions makes them more comprehensible and natural, moving an important step further towards navigation interfaces that are cognitively more adequate. Third, we present the first implemented route description generation algorithm that takes users' prior knowledge into account. To evaluate the adequacy of these combined ideas we present results obtained from a human-based experiment of our approach.

The architecture we aim to construct consists of several components, including salience measures of geographical features, i.e., landmarks and streets, as well as a natural language generation technique that integrates the former into textual descriptions. As a first component, we consider landmarks and their associated salience. Landmarks are prominently present in human route descriptions, but they are no concept in spatial databases. As discussed previously, they are also context- and route-dependent. Accordingly, multiple approaches to landmark selection have been suggested. None of them has been taken up by commercial systems because of the lack of input data for these methods.

The only known method that is promising to be applicable on a large scale is the one based on rated categories (Duckham, Winter, & Robinson, 2010), which is therefore also applied in this paper. However, instead of relying on identical salience ratings for all instances of one category (e.g., all fast food restaurants) we suggest here an additional, novel method for further differentiation within each category. This additional method is based on the frequency of use of the particular names of landmarks. The underlying assumption is that frequently used names belong to well-known landmarks. A freely available data source for frequently used words is the Google Web 1T corpus (Brants & Franz, 2006), which contains 1- to 5-grams—sequences of one to five words occurring more than 40 times in Google's index of the web. Google *n*-grams are derived from about one trillion words of English text. Here, the Google Web 1T *n*-gram corpus is employed to calculate the frequency of landmark names mentioned in Web documents. The salience of an individual landmark is computed from a combination of the normalized frequency of itself within its category and the rating of its category.

As a second component, we consider salience within the street network. While streets are natural conceptualizations of the street network for people, they do not form elementary objects in spatial databases. Rather, spatial databases represent a street network by nodes for street intersections and edges for connecting street segments. A pre-processing step is required to re-establish streets as sequences of nodes and edges. This step can be based either on a name attribute of the edges (if given), combining all consecutive edges with the same name, or it can be based on the good continuation prin-

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ciple (Thomson & Richardson, 1999), which is a grouping of all consecutive edges below a certain deflection angle. The latter can be computed even on data where street name attributes are lacking or are incomplete. To compute the salience of streets it has been suggested (Jiang, Zhao, & Yin, 2008; Tomko et al., 2008) to use betweenness centrality (Freeman, 1977), which characterizes how often a network element (originally nodes, but it can be extended to edges or even to streets) lies on all the shortest paths in a network. This means it characterizes how often these network elements are used when travelling in the network, such that an element of high betweenness centrality is one that is often used, or—so the reasoning—relatively well known.

As a third component, we extracted from a corpus of human-authored route instructions typical linguistic expressions associated with spatial situations, and use these variants to generate variable and more natural texts. This is not only in accordance with variation being a general stylistic rule of good writing, but also with findings confirming that humans prefer variation in system-generated language to repetitiveness (Foster & Oberlander, s.d.; Belz & Reiter, 2006).

The following sections will present in more detail first the individual components that feed into our algorithm and then present the algorithm itself.

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## 4. PREPROCESSING SPATIAL DATA

This section will introduce our main mechanisms for generating spatially-informed route instructions: the processing of streets, landmarks and routing algorithm.

### 4.1. Streets

A street is defined as a linear geographic entity that stretches in two dimensional space, and is often given a unique name. In this work a good continuation representation of the street network is utilized (Thomson & Richardson, 1999), because of lack of data on street names. In this representation segments are joined according to the principle of good continuation, in which every segment at each end chooses one most suitable neighboring segment with smallest deflection angle, and this process goes on until the deflection angle is greater than a preset threshold (Jiang et al., 2008). This representation satisfies human navigation strategies by its natural grouping: street segments with low deflection angle are considered as one street in this representation, such that individual turning instructions become redundant and unnecessary.

To identify salient streets in the street network, betweenness centrality is used. In a graph $G = (N, E)$ consisting of $N$ nodes and $E$ edges, let $\left|SP_{jk}\right|$ denote the number of shortest paths between nodes $j, k \in N$, and

$\left|SP_{jk(i)}\right|$ the number of shortest paths leading through node $i \in N$. Betweenness centrality of the node $i$ is defined as follows (Freeman, 1977):

$$C_i^b = \sum_{\substack{j,k \\ j \neq k \\ j,k \neq i}} \frac{\left|SP_{jk(i)}\right|}{\left|SP_{jk}\right|} \tag{1}$$

Betweenness centrality can also be applied to edges by replacing $SP_{jk(i)}$ by $SP_{jk(e)}$, the number of shortest paths from $j$ to $k$ containing the edge $e$, or to streets. Then betweenness centrality describes the degree to which an edge (street) falls on the shortest path between two other edges. In contrast to (Tomko et al., 2008) here the betweenness centrality of a street is computed via the centrality of its edges. Their centrality measures are then accumulated for the street.

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### 4.2. Landmarks

The salience of landmarks is ranked here according to two aspects: the average salience of the set of elements of a category in a business directory (Duckham et al., 2010), and the novel approach described above to cater for the variations within the category. The categories are assessed by their average nature for navigation purposes, which generally indicates how appropriate individuals of this category are for route instructions. Categories may be ranked differently for specific user groups (for example, car drivers and pedestrians). Therefore, categorial salience may vary in different contexts. Individual salience can be ranked by using web $n$-gram data. The overall landmark salience, *LandmarkSal*, is then the combination of these two aspects, where *CategorySal* and *IndividualSal* are the categorial salience and individual salience, respectively:

$$LandmarkSal = CategorySal \times IndividualSal \tag{2}$$

In addition, the salience of landmarks is influenced by their visibility; in other words, landmarks used in good descriptions need to be visible from approaching directions (Michon & Denis, 2001; Caduff & Timpf, 2008; Winter, 2003). In the experimenal evaluation of this paper, we apply only a buffer, filtering the landmarks that are near the route. Refinements of this implementation are always possible.

### 4.3. Routing Algorithm

Dijkstra's algorithm (Dijkstra, 1959) or variants thereof such as the A* algorithm (Hart, Nilsson, & Raphael, 1968) compute the path of minimal

costs for any cost function with non-negative values. This cost function is conventionally the travelled distance or travelled time. Other cost functions that might be desired in special contexts have been developed as well, such as the simplest route (Duckham & Kulik, 2003).

The following model is independent of a specific routing algorithm or cost function. It is not concerned with computational efficiency, and not even with the properties of the selected route, i.e., the applied cost function. The fact that specific cost functions satisfy specific wayfinding contexts requires integration of choosing an appropriate cost function in the future, but for the development of our model any routing algorithm will suffice.

Route segments are divided by turning points and are treated as units bearing information on the current street, landmarks, the distance traveled on a segment, the absolute direction of travel (east, west, etc.) and the relative direction of travel (left, right, etc.). Routes are generated by a sequence of segments, where first all necessary information is inferred from an underlying data set, and subsequently formatted into a stream:

1. Calculate per segment: (a) distance traveled, (b) absolute direction, (c) relative direction
2. Write: (a) turning point, (b) landmarks (plus details), (c) street (plus details), (d) distance traveled, (e) absolute direction, (f) relative direction

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## 5. REALIZATION OF ADAPTIVE ROUTE DESCRIPTIONS

After a route has been obtained and annotated with salience scores of landmarks and streets, we need to determine the level of granularity required for a user and realize the instructions in natural language.

### 5.1. Instruction Generation in the Context of Familiarity

Each route we generate is annotated with the familiarity of the user, either "familiar" or "unfamiliar." From this, we decide to either give turn-by-turn or destination descriptions. Turn-by-turn is the mode of description used currently as best practice for users who are entirely unfamiliar with the route and the area. In turn-by-turn descriptions, we verbalize each segment contained in the route without any further contraction or summarization that goes beyond the segmentation mechanisms introduced earlieron. The highest ranked landmark along a segment is included in the description of the segment if its ranking score is above a pre-specified significance threshold. Street salience is neglected for the verbalization of turn-by-turn descriptions, since typically only one street is relevant per segment such that no choice has to be made.

**Algorithm 1.** Algorithm for realizing destination descriptions

```
function GENERATEDESTINATIONDESCRIPTION(landmarks, streets)
    if familiarity == familiar then
        for each landmark do
            if landmark.getWeight ⩾ threshold then
                Landmark ← known_landmark
            end if
        end for
        for each street do
            if street.getWeight ⩾ threshold then
                Street ← known_street
            end if
        end for
        if known_landmark.getWeight ⩾ threshold then
            destination_description to landmark
        else destination_description over street
        end if
        route ← remainder
    end if
end function
```

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In contrast, destination descriptions are realized whenever a route enquirer possesses prior knowledge of the environment. In this case, we summarize or omit certain parts of the route which the enquirer is assumed to be able to infer. An algorithm for generating destination descriptions is displayed in Algorithm 1. It starts by traversing the current route identifying all landmarks that have a weight higher than a specified threshold (salience measures show a long-tailed distribution) and all streets which have a salience value (based on betweenness centrality) higher than the threshold (which is the average betweenness centrality value). Whenever it finds landmarks or streets fitting these characteristics, it produces a destination description either to the landmark or over the street, depending on which of the two was identified as more salient in their class. The algorithm prefers mention of landmarks where a landmark and a street are equally salient in their respective classes. This procedure is repeated until either the route is entirely verbalized or no more landmarks or streets with specified salience thresholds can be found.

### 5.2. Linguistic Realization

One important goal of this research was to enhance the linguistic quality of our generated instructions, and improve on the repetitive patterns typically found in automatically generated descriptions. To achieve variation that is not arbitrary, but reflects human linguistic behaviour, we collected and analyzed a

corpus of human-written route descriptions for drivers in urban environments. As a first step towards analysis, we extracted from the corpus all $n$-grams that could be used to verbalize different constituents of instructions, and mapped them onto different instruction types, "turning" or "passing," for example. This resulted in a number of surface strings that could be used to express a particular concept. Varying between these alternatives allows us to produce stylistically better and more variable instructions. We use $pCRU$, introduced in the following, to control the arising variation.

### 5.3. *pCRU*

Probabilistic context-free representational underspecification ($pCRU$) (Belz, 2008) is an approach aiming to resolve the non-determinacy that arises between a semantic representation, i.e., an input to a language generation system, and all its possible linguistic surface forms. Natural Language Generation (NLG) is concerned with transforming a semantic representation (or logical form) of a message to be communicated into a string of words by passing it through a natural language generator that performs all required mappings between the two formats. As an example of the non-determinacy that can arise, consider the following logical form, which serves as an input to the KPML generation system (Bateman, 1997), which we use for the current work.

```
(v0 / |space#NonAffectingOrientationChange| :SPEECHFUN
  :|actor| ( hearer / |person| ) :VERB :PHORICITY
    :|space#direction| (sd / |space#GeneralizedLocation|
      :|space#hasSpatialModality| (lp / |space#LeftProjection|)))
```

This semantic representation expresses a simple turning action to the left. A small subset of possible realizations includes ["Turn left," "Turn to the left," "You are turning left," "Left," and "Go left"], which differ in their choice of speech function (imperative vs. declarative), tense (present vs. present continuous), the phoricity of the direction attribute (phoricity means prepositional phrase vs adverbial phrase), or the choice of verb. In accordance with the $pCRU$ framework, we formalize such variation as a probabilistic context-free grammar (PCFG), consisting of a set of terminal symbols $W$, a set of non-terminal symbols $N$, a start symbol $S \in N$ and a set of production rules $R$ of the form $n \rightarrow \alpha$, with $n \in N, \alpha \in (W \cup N)^*$ and $W$ and $N$ being disjoint. As an example, the start symbol $S$ of a $pCRU$ could correspond to an instruction type, for example, 'turning.' The set of non-terminal symbols $N$ could correspond to `:SPEECHFUN`, `:VERB` and `:PHORICITY` shown in the logical form above and the set of terminal symbols $W$ could correspond to different expansions of the non-terminal symbols, for example 'assertive' or 'directive' for `:SPEECHFUN` or 'turn,' 'go' or 'bear' for `:VERB`. This yields variation such as in the above example.

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In order to capture certain frequencies of occurrence of the collected linguistic variants, we attach probabilities to the expansion rules in the PCFG that correspond to the probabilities extracted from the corpus of human descriptions.

### 5.4. Referring Expressions

We generate contextually-sensitive referring expressions by controlling the articles in route descriptions. As an example, consider the sequences (1a)-(1b) and (2a)-(2b) below. In (1a)-(1b), we first identify a new object and then treat it as identifiable in the next sentence. In (2a)-(2b), the second sentence substitutes the action of turning mentioned in the previous sentence by "this," i.e., construing it as identifiable.

(1a) "There will be a car park in front of you."
(1b) "Take a left onto Southgate Avenue, when you get to the car park."
(2a) "Turn left at the car park."
(2b) "This will lead you onto Southgate Avenue."

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### 5.5. Aggregation

We aggregate messages either by a conjunctive relation 'and' (3a) or by a sequence relation 'then' (3b).

(3a) "Turn left into Grattan Street and follow it until you see the university on your right."
(3b) "Follow Grattan Street for 500 metres, then turn left."

## 6. IMPLEMENTATION AND EXAMPLES

After having introduced in detail our mechanism for adaptive route generation and realization, this section will present a system architecture for implementation and several concrete examples.

### 6.1. System Overview

Our architecture is organized into three separate components (cf. Figure 1), based on (Reiter & Dale, 2000). As mentioned earlier, a natural language generation system transforms a semantic representation or logical form into a string of language. In our system, the first component, *text-planning*, is entered as a result of a user requesting a route from some source to some des-

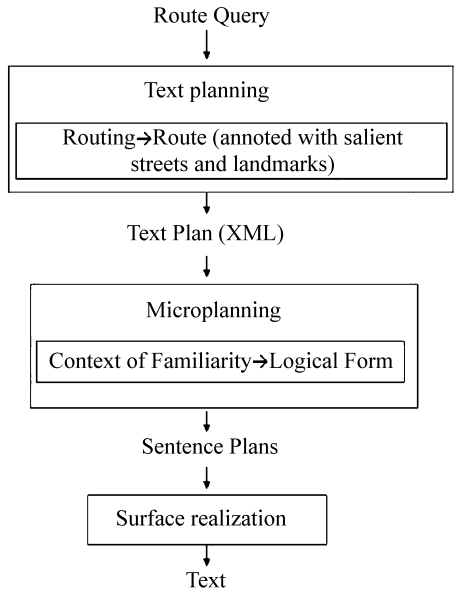


***Figure 1.*** System architecture.

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tination. This component first computes the requested route using a shortest-path algorithm and splits it into several segments. Next, the route is annotated with the salience scores of streets and landmarks that are associated with the route. An XML-based route plan (or text plan, from an NLG perspective) is passed on to the next module.

In the second module, *Microplanning*, we plan the structure of individual instructions. To this end, we transform each of the route segments contained in the text plan into logical forms that correspond to sentences and can be passed to a generator. For this purpose, we need to take the current user's prior knowledge into account to choose an appropriate level of granularity, i.e., give a turn-by-turn description or a destination description. We call logical forms passed on from this component sentence plans. The last component, *Surface Realization*, passes sentence plans on to an NLG system and presents the user with a verbalization of the segment.

## 6.2. Implementation

As a first step towards route generation, the street network data of Melbourne's central business district was collected from OpenStreetMap.[1] Street segments were merged into streets based on good continuation. The threshold

[1] www.openstreetmap.org.

**Table 1.** Expert rating of two categories: "Libraries" and "Schools"

| | Libraries | | Schools | |
|---|---|---|---|---|
| | Suitability | Typicality | Suitability | Typicality |
| Physical size | Suitable | Many | Highly | Most |
| Proximity to road | Somewhat | Many | Highly | Most |
| Visibility | Suitable | Most | Highly | Many |
| Difference from surroundings | Suitable | Many | Suitable | Many |
| Ubiquity | Ideal | Most | Ideal | Many |
| Nighttime vs. daytime salience | Never | Most | Somewhat | All |
| Permanence | Highly | Most | Highly | Many |
| Length of description | Highly | Many | Highly | Most |
| Spatial extents | Highly | Many | Suitable | Many |
| Overall score | 19 | | 23 | |
| Salience | 0.375 | | 0.475 | |

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chosen for this merging process was based on the definition of "straight" by (Klippel & Montello, 2007), who investigated cognitive judgments of turn directions in a grouping experiment. In order to highlight the subset of salient streets from the dataset, betweenness centrality was applied. The merging of street segments as well as the network analysis was performed with the space syntax software Mindwalk (Figueiredo, 2005). After computing the betweenness values of streets, those that had a value higher than average were selected as salient streets.

As a next step, a directory of 1434 businesses and other points of interest within the chosen area was obtained from WhereIs.[2] Salience of landmark categories of this directory was assessed on the basis of nine criteria of category suitability and typicality according to (Duckham et al., 2010). Table 1 shows two of these assessments, for the categories of "Libraries" and "Schools." Individual salience was calculated by normalizing individual web $n$-gram counts against maximal counts within its category. For example, "Galilee Regional Catholic Primary School" gains 61 counts in the 5-grams, and the maximal count of category "Schools" is 232,738, hence the individual salience of "Galilee Regional Catholic Primary School" is 0.000262. According to Equation 2, its salience is the product of these two values, 0.000124. A buffer of 70m was chosen to select landmarks along the chosen route.

For each route, XML files were generated, containing street, landmark and navigation information for each segment along the route. Both nodes and edges of a route graph can be supplemented with descriptive information such as landmarks. Routes are then interpreted with respect to the user's

[2]www.whereis.com/products/for-your-business/whereis-api

familiarity, and verbalized in natural language. An example of a segment in an XML file is shown in Figure 2.

### 6.3. Examples

For comparison of the different instruction types we will evaluate in the next section, several types of instructions are displayed in Tables 2 and 3. All of them describe the route from the "Richmond South Post Office" to the "Richmond Cricket Ground" in Melbourne. A map is provided in Figure 3.

## 7. EVALUATION

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To evaluate our proposed approach, we set up a user study to collect ratings of route descriptions for car drivers and investigate the following questions: (1) whether humans would perceive our descriptions as equally natural as human descriptions, and (2) whether our descriptions would be perceived as equally helpful as human descriptions. We hypothesized that both points would be confirmed. Another goal was to investigate how our architecture could be improved, particularly with regard to the linguistic realization of routes, and the use of landmarks and street names.

### 7.1. Method

Two different questionnaires were designed and distributed by email to participants of this evaluation. The first questionnaire provided twelve sets of turn-by-turn descriptions, and the second questionnaire included six sets of destination descriptions. Each set includes one description automatically generated by our system (called CD for computer-generated description) and one human description (called HD for human description). The first questionnaire contained additionally a turn-by-turn description per set generated by an online routing service, Google Maps (called GD for Google description). We are not aware of any commercial or online routing service that provides destination descriptions, hence there are only CDs and HDs for the destination description set. Sources and destinations were selected from locations in Melbourne, Australia.

The procedure of the evaluation of both questionnaires was as follows. At the beginning, participants indicated their familiarity with the environment, choosing a value from among "highly familiar," "somewhat familiar" and "not familiar." Afterwards, they read through all route descriptions, answering for each the following set of questions:

(1a) "Which of these route descriptions do you think are automatically (computer-) generated?"

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```
<segment turning_point="false">
  <landmarks possible_decision_point="false" weight="0.000124"
  dd_weight="0.705000" named="true" distance_from_route="32.980345"
  distance_from_last_segment="116.159052"
  distance_from_next_segment="32.980345">
    <name>Galilee Regional Catholic Primary School</name>
    <landmark_type>Schools</landmark_type>
    <suburb>South Melbourne</suburb>
    <egocentric_landmark_position>left</egocentric_landmark_position>
    <relation_to_decision_point>before</relation_to_decision_point>
  </landmarks>
  <street weight="0.001800">
    <name>Bank Street</name>
    <street_type>residential</street_type>
    <street_feature after_distance_traveled="0.0"
    possible_decision_point="true" length="86.537511"
    junction="Montague Street">
        <feature_specification>null</feature_specification>
    </street_feature>
  </street>
  <distance_traveled>86.53751144988007</distance_traveled>
  <cardinal_direction>east</cardinal_direction>
  <direction_of_travel>front</direction_of_travel>
</segment>
```

***Figure 2.*** An XML segment of a computed route.

**Table 2.** Comparison of different descriptions: Google Maps and human

| Description |
|---|
| Human turn-by-turn description<br>"Drive west one block, and turn right on Wangaratta St. Drive in a northerly direction and turn left on Tanner St. Take the first right onto Alfred St, drive until you come to Rotherwood St. Drive a few blocks up to the end of Rotherwood St and turn left onto Bridge Rd. Drive westward on Bridge Rd, crossing Hoddle St, where Bridge Rd turns into Wellington Parade. Turn left at the traffic lights on Powlett St. Follow the road, driving through the park area till you get to the Richmond Cricket Ground, passing the MCG on your right." |
| Human destination description<br>"The RCG is located adjacent to Punt Rd next to the Richmond, small AFL club in the parkland close to the MCG." |
| Google Maps turn-by-turn description<br>"Head south on Elizabeth St toward Bourke St (270 m). Turn left at Collins St (700 m). Turn right at Exhibition St (230 m). Turn left at Flinders St (230 m). Continue onto Wellington Pde (400 m). Turn right at Jolimont St (210 m). Continue onto Jolimont Tce. Destination will be on the right (64 m). |

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**Table 3.** Comparison of different descriptions: System-generated descriptions

| Description |
|---|
| System turn-by-turn description<br>"Follow Swan Street to Richmond South Post Office for 52 metres. Take a left after the Richmond South Post Office, and take a right onto Woodlawn Street. At this point, go past a car park on the left. Cross the next junction at Normanby Place, and cross the next junction at Moorhouse Street. Drive past traffic lights on the right, and cross the next junction at Punt Road. This will then lead onto Wellington Parade. Go straight over junction. Cross the next junction, when you get to Vale Street. Go into East Melbourne. Take a slight left after the East Melbourne Post Office. At this point, go past traffic lights on the right. Head straight over junction, and take a turn after the traffic lights. Take a left before the Barbeque, and after the Barbeque, take a slight right. At this point, pass the Richmond Cricket Ground on the left and continue for 62 metres." |
| System destination description<br>"Head to the East Melbourne Post Office that is on Wellington Parade. Take Rotherwood Street and then go over Wellington Parade. You will come to the Richmond Cricket Ground." |

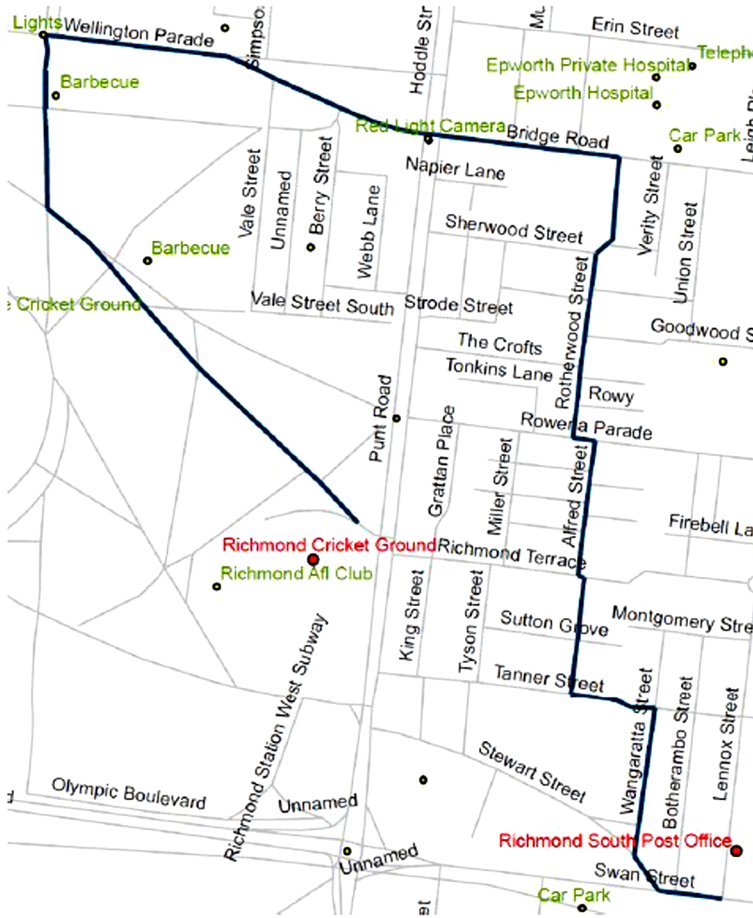


***Figure 3.*** The route from 'Richmond South Post Office' to 'Richmond Cricket Ground' in Melbourne. (color figure available online)

(1b) "Why do you think they are computer-generated?"
(2a) "Which of these descriptions do you think is the most useful? (Which of these descriptions would you prefer?)"
(2b) "Why do you think it is most useful?"

All types of users evaluated descriptions for both familiar and unfamiliar users. We used question (1a) to assess the naturalness of our descriptions and question (2a) to assess their acceptability and usefulness. In each case we were able to draw a direct comparison with human as well as online-generated descriptions. For both questions, we expected that our descriptions would be rated closer to human descriptions than the online-generated descriptions, and

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thereby reflect the adaptive features we supplemented them with. Questions (1b) and (2b) aimed at providing us with a better understanding of the participants' judgments. We may use these responses to improve our system in the future.

### 7.2. Participants

Twenty-three participants took part in the evaluation of the turn-by-turn questionnaire and 15 participants took part in the evaluation of the destination description questionnaire, their ages ranging between 20 and 60 years. Participants were asked to answer all questions on a computer; they were not required to drive the routes. Thus, the descriptions were not given in-situ.

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### 7.3. Results: Naturalness and Helpfulness

This section presents the results of questions (1a) and (2a) that indicate the naturalness and helpfulness of our descriptions.

*7.3.1. Naturalness: Identification of Computer-Generated Descriptions.* For turn-by-turn descriptions, participants were able to identify 36% of CDs and 94% of GDs. 4% of HDs were falsely classified as machine-generated. For destination descriptions, the difference between CDs and HDs that were classified as machine-generated is smaller, which is 42% and 34%, respectively. The exact percentages are shown in Table 4. Since the data did not come from a normal distribution, we tested for statistical significance using the Wilcoxon signed-rank test. The differences between CD and GD, CD and HD, and GD and HD are all significant at $p < 0.01$.

*7.3.2. Helpfulness: Identification of the Most Useful Description.* For turn-by-turn descriptions, participants considered 42% of all HDs useful and 26% of all CDs. GDs were considered useful by 30% of the participants. Notably, there is a significant difference between the rating of familiar users (only 7%

**Table 4.** Descriptions classified as machine-generated

| | CD (%) | GD (%) | HD (%) |
|---|---|---|---|
| TBT familiar | 40.63 | 91.67 | 5.21 |
| DD familiar | 40.30 | / | 35.53 |
| TBT unfamiliar | 32.78 | 96.67 | 3.33 |
| DD unfamiliar | 49.64 | / | 34.55 |
| TBT all | 35.51 | 94.33 | 3.99 |
| DD all | 42.22 | / | 34.44 |

**Table 5.** Descriptions perceived as most useful

| | CD (%) | GD (%) | HD (%) |
|---|---|---|---|
| TBT familiar | 7.29 | 41.67 | 47.92 |
| DD familiar | 53.26 | / | 46.02 |
| TBT unfamiliar | 36.78 | 24.44 | 39.44 |
| DD unfamiliar | 64.85 | / | 32.74 |
| TBT all | 26.45 | 30.43 | 42.39 |
| DD all | 65.55 | / | 32.22 |

found turn-by-turn CDs useful) and unfamiliar users (37% found turn-by-turn CDs useful). In the case of destination descriptions, CDs were preferred to HDs by all participants by 66%. All percentages are shown in Table 5. The differences are not statistically significant.

*7.3.3. Discussion.* With regard to the perceived naturalness of instructions, participants were able to correctly classify 36% of CDs as machine-generated, which means that 64% of all CDs were considered as natural as their human counterparts. This stands in strong contrast to the 94% identification rate of GDs and suggests that our proposed approach for enhancing the naturalness of route descriptions is indeed promising. Even though the identification rate was higher for destination descriptions (42%), a large part of human destination descriptions was also classified as machine-generated (34%). This indicates that it is harder to distinguish CDs from HDs in destination descriptions than in turn-by-turn descriptions. Hence we can say that our generated destination descriptions are more natural and closer to human destination descriptions than our turn-by-turn descriptions.

With regard to the helpfulness of instructions, we can observe that although almost all GDs were identified as machine-generated, 30% of them were still considered useful by participants. CDs were considered useful by 26% of participants. These results stem from the fact that our system received very low rankings for turn-by-turn descriptions by familiar participants (only 7%), but they also interestingly indicate that computer-generated instructions are not necessarily automatically rejected by participants. The difference between HDs and GDs for familiar participants was smaller; the preference of HDs was only 6%. Unfamiliar participants, in contrast, preferred CDs to GDs (37% and 24%, respectively) and rated them only slightly worse than HDs (39%). For destination descriptions, both familiar and unfamiliar users show higher preference for CDs than HDs; for unfamiliar participants this difference is even five times larger than for familiar participants. One possible reason is that CDs are often longer than HDs, meaning that more information is provided in CDs, which is what unfamiliar participants require.

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On the other hand, some familiar people preferred "short and sharp" descriptions. For the interpretation of these results, it is important to consider that participants rated the usefulness of descriptions without having followed them. Given this fact, we will need to treat the unfamiliar users' ratings with a dose of caution: since we cannot assume that they have very good knowledge of the route itself, their rating may still be influenced by their rating of the first question, i.e., they may rate descriptions more useful that they perceive as well written. This is less likely to be the case for familiar users. An experimental setting in which participants would have been required to use the different routes for wayfinding would have provided a more objective measure of the usefulness of the descriptions. A further limitation is that our results were obtained from a relatively small sample. For certain situations in particular, such as the distinction of familiar and unfamiliar users, we did not test with a representative sample, which is often taken to be $\geq 20$ participants. This is also true for the evaluation of destination descriptions. For the same reason we did not evaluate gender differences, which would have required to split our participants into two groups of sample sizes below 20. However, there are still certain tendencies we can observe. Participants of all degrees of familiarity perceive our turn-by-turn descriptions as considerably more natural than Google-generated descriptions, and rate destination descriptions as lower, but generally close, to human descriptions. We can conclude from this that verbalizing route descriptions with variable surface forms enhances the naturalness of descriptions and is rated positively by humans. While future work will need to address the question of how turn-by-turn descriptions can be improved, we can still see that our destination descriptions were rated as more useful than their human-written counterparts by both groups of users.

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### 7.4. Results: Motivation of User Ratings

Questions (1b) and (2b) asked participants to motivate the way they rated descriptions in questions (1a) and (2a). This section addresses the main points addressed by participants.

*7.4.1. Use of Street Names.* The use of street names in CDs was better accepted for destination descriptions than turn-by-turn description. However, participants commented for both types that they would expect more street names. Two participants commented positively on the use of known streets in CD destination descriptions, which highlights the advantage of identifying prominent streets by centrality measures.

*7.4.2. Selection of Landmarks.* The main criticism in the selection of landmarks was about using unsuitable landmarks, such as barbecue (as found in many Australian parks). Although such categories of landmarks are ranked

very low by experts for driving purposes, the long tail of zero and minimal salience drags the selection threshold to an even lower value. Therefore, the threshold applied (i.e., the average of landmark salience) becomes inappropriate for excluding unsuitable landmarks. Furthermore, some of the participants preferred human descriptions because they included landmarks that showed local knowledge of the area, for instance, the local football club.

*7.4.3. Automatically Generated Language.* The system instructions were perceived as sometimes too long, verbose or complex, including too much detail and redundancy. In this way, they were judged as sometimes not easy enough to remember. On the other hand, some users also appreciated the descriptive detail of the instructions.

### 7.5. Potential Improvements

The feedback from participants and our own observations suggests the following improvements:

- The thresholds of landmark selection in route descriptions needs further investigation to exclude redundant and unsuitable information.
- The language of CDs needs to be simplified and redundancy and ambiguity needs to be removed.
- The spatial data used to generate route descriptions may also affect system performance, so other data sets may be compared.
- The salience value of streets used in destination descriptions may be transferred to turn-by-turn descriptions.

## 8. CONCLUSIONS

We presented a concept and an architecture for generating adaptive route descriptions in urban environments, at different levels of granularity, by integrating features from cognitive science and linguistics. These features include the design principles and linguistic properties of human route descriptions. Our approach is unique in several ways: (a) it provides an integration of different models of spatial salience and natural language generation, (b) it presents a novel mechanism for realizing route description texts, (c) it provides the first implemented algorithm that takes users' prior knowledge into account, and (d) an evaulation revealed a strong preference of our descriptions over web-generated descriptions and showed that they were as equally well perceived as human descriptions—or even better in the case of destination descriptions. Future work can address the following points:

- User models can be made more fine-grained to include several degrees of familarity in between the two extremes "familiar" and "unfamiliar."

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Descriptions could then contain mixtures of turn-by-turn and destination descriptions to give just as much guidance as the current user requires, or alternatively, adapt the content of the route, generating, e.g., the fastest route, or the easiest route to travel or describe.

- In addition to the current in-advance instructions, our architecture could be extended to provide in-situ descriptions. This would make it more suitable to online navigation, and be supplemented with an evaluative user study in a real navigation setting.
- The system can be supplemented with further modalities, such as maps and speech. This would provide users with additional visual support and let them choose their preferred mode of communication: text, speech, or map. Such a feature would also address the amount of attention users are able to allocate to instructions (drivers vs. pedestrians).
- Machine learning techniques can be used to support more complex behavior of the system, such as integration of fine-grained user models, mixture of description types, multiple modalities, as well as the currently present features—salient streets, landmarks and natural language. Using machine learning, the system can learn to optimize its decision making process and therefore adapt more flexibly to new situational circumstances, similar to (Cuayáhuitl, Dethlefs, Frommberger, Richter, & Bateman, 2010).

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