Towards a Classification of Route Selection Criteria for Route Planning Tools

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Abstract. Route planners are tools that support the navigator in selecting the best route between two locations. Solving a route choice problem involves sorting and ranking of alternatives according to underlying evaluation criteria and decision rules. Using an appropriate classification of route selection criteria in the user interface is an important ingredient for user friendly route planners. The paper presents a method for assessing a hierarchical structure of route selection criteria for bicycle route planning tasks along with data from two empirical studies. The first study investigates route selection criteria that are relevant for bicycle navigation in urban environments. The second study reveals preferred classification schemata for these criteria. The presented methodology can be adopted for other transportation domains, such as car or pedestrian navigation.

Keywords. Route selection criteria, classification, spatial decision support, user interface design, bicycle navigation

1 Introduction

Most of the current bicycle route planners apply a fixed criterion optimization function (Ehlers et al. 2002; MAGWIEN 2004) or offer preference statement functionality only between a limited set of route selection criteria, such as short, fast, scenic, or avoiding slopes (Rad.RoutenPlaner 2003; MVEL 2004). Previous work gives evidence that human navigators are not exclusively shortest path or least time decision makers (Golledge 1997; Hyodo et al. 2000; Hochmair 2004). Thus, the user of a route planner should be offered the possibility to select between a larger range of route selection criteria. We address route selection within the framework of multiattribute decision making (MADM), which involves a single objective and a limited number of choice alternatives (Malczewski 1999). The objective "find best route" can be measured in terms of several evaluation criteria. The first study of this paper will reveal the relevance of various route selection criteria with respect to this objective.

Despite the user's demand for additional route selection criteria in bicycle route planners, the number of offered criteria from which the user can select must be kept small due to limited human cognitive capacities in information processing (Miller 1956; Rosch 1978). Thus, designers of a user interface need to find a compromise between simplicity and more detailed functionality. An appropriate classification of route selection criteria provides the basis for intelligent user interfaces that adopt their functionality to the user's current demand for detail: Preference statements between a small number of more general higher-level attributes will result in a good route suggestion after a small number of interactive steps. Additional preference statements between more detailed lower-level criteria would allow the decision maker to refine her query. The second empirical study in this work investigates how participants hierarchically structure a given set of 35 route selection criteria. These findings provide the starting point for describing a method which derives a single final classification from a set of given classification suggestions, and where the final classification contains a reasonable number of criterion classes and provides a good "average" classification from the suggestions.

The paper is structured as follows: Sections 2 and 3 describe two empirical studies about relevant route selection criteria for cyclists and their suggested classifications. Section 4 presents a guideline for deriving one single final classification from a set of given classification suggestions. Section 5 introduces a method for intra-class weighting of member attributes of a criterion class, and section 6 summarizes the findings and presents directions for future work.

2 Study 1: Evaluation Criteria

The set of evaluation criteria included in a decision support system should be complete to cover all the important aspects of the decision problem (Keeny and Raiffa 1993; Malczewski 1999). So far route selection criteria for cyclists have only been roughly sketched in the context of very specific applications, such as urban planning (Hyodo et al. 2000), or Web based bicycle route planning for tourists (Ehlers et al. 2002). To provide a useful classification of route selection criteria, a more comprehensive list of bicycle route selection criteria is required, which we achieved by an internet survey. The participants in the survey took the role of a cycling tourist in an unfamiliar city who wants to find the best route to a given restaurant. Participants were asked to enter the criteria they would consider in their route choice as free text in the questionnaire. The importance of each mentioned route selection criterion had to be stated by a score value between 1 (quite unimportant) and 4 (very important). Table 1 shows the summary of the 42 filled questionnaires, i.e., the mentioned route selection criteria ranked after their summed score values. Numbers in brackets indicate how many times a criterion has been mentioned. The most prominent route selection criterion was "bike lane" (mentioned by 78% of the participants), followed by "short", "sights", and "avoid heavy traffic".

Criterion	Score	Criterion	Score
bike lane	114 (33)	main road	6 (2)
short	66 (20)	no wrong enter of one-ways	6 (2)
sights	65 (25)	lighted at night	6 (3)
avoid heavy traffic	65 (20)	safe	6 (2)
parks	31 (13)	avoid tunnel	6 (2)
side streets	27 (8)	straight	5 (2)
avoid steep street segment	26 (10)	avoid city center	5 (3)
simple	25 (7)	shopping streets	5 (4)
fast	20 (7)	city center	5 (2)
good signage	19 (6)	avoid public transport	4 (1)
good street condition	17 (7)	nice bridges	4 (1)
lakes and rivers	16 (7)	avoid roundabout	3 (1)
prominent buildings and LM	13 (5)	avoid busy intersections	3 (1)
few intersections	9 (4)	avoid controls by authorities	3 (1)
snack bar	9 (3)	nice view	3 (1)
safe area	9 (3)	interesting route	2 (1)
few traffic lights	8 (2)	avoid construction sites	1 (1)
avoid pedestrian area	7 (3)		

Table 1. *Route selection criteria for bicycle navigation in urban environments*

The route selection criteria in Table 1 are of varying generality. Some denote more general demands, such as "safe" or "interesting" and can be split into several lower-level attributes. Other ones, such as "short" or "few intersections", are more focused and describe a measurable effect.

3 Study 2: Classification Task

The decision maker's objective ("find best route") and the related route attributes form a hierarchical structure of evaluation criteria. We expect that an appropriate classification which pre-sorts the lower-level criteria with their effects on a route into criterion classes will reduce the user's mental effort in stating her preferences. Finding an adequate value function over a set of route selection criteria, which is needed for the implementation of a route search algorithm that provides trade-off functionality, requires a complete set of measurable lower-level attributes. The presented classification study will provide such a comprehensive set as part of its results. This paper will not discuss the assessment of value functions, as the importance values between the involved attributes depend on the range of attribute scores of choice alternatives at hand (Keeny and Raiffa 1993) and on the user's subjective thresholds for accepting attributes scores (Srinivasan 1988).

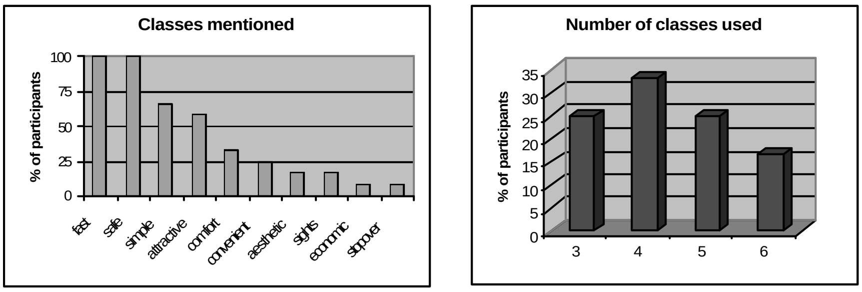
Cluster analysis (Hartigan 1975) sorts cases (e.g., higher-level criteria) into groups of clusters based on selected characteristics, so that the degree of association is strong between members of the same cluster. However, cluster analysis cannot replace empirical investigation as the best number of criterion classes to be used in a route planner, as well as the cases that should be clustered, are not known a priori. Factor analysis (Backhaus et al. 1996) attempts to identify underlying variables (factors) that explain the patterns of correlations within a set of observed variables. The disadvantage with factor analysis is that the method would require explicit route suggestions to be evaluated by the participants, which would affect the results.

3.1 Task description

The list of route selection criteria from Table 1 was handed out to 12 participants who were asked to classify all criteria into either three, four, five, or six classes. The participants could either re-use criteria names for class names or create their own class names, if none of the terms in the list matched their concept of a particular class in mind. Further, the participants had to mark, whether a lower-level criterion was positively (+) or negatively (-) oriented towards the class. As lower-level attributes could be assigned to several classes by each participant, an attribute could be stated as being positively oriented with one class and being negatively oriented with another. For example, participants stated that the criterion "avoid pedestrian area" makes a route faster (positive orientation wrt. the class "fast") but at the same time less attractive (negative orientation wrt. the class "attractive").

3.2 Results

Participants suggested ten different class names in the classification study (Fig. 1a). The class names "fast" and "safe" were mentioned by all participants, followed by "simple" (67%) and "attractive" (58%). Most participants (33%) used four classes (Fig. 1b). Thus, four should be an appropriate number of classes used in the final classification. It is interesting that none of the participants suggested the prominent criterion "short" as its own class. This finding may be explained by the fact that "short" cannot be decomposed into further attributes.



(a) (b)

Fig. 1. *Classes mentioned in the classification task (a), and distribution of used number of classes (b)*

Next we analyzed for each class the membership structure of included criteria. Fig. 2 shows a part of the membership structure for the classes "fast" and "safe". A value of 100% for an attribute a in class C means that in all classifications where class C has been mentioned, attribute a has been assigned to class C. It does therefore not necessarily mean that all participants assigned attribute a to class C (as not all participants may have mentioned class C).

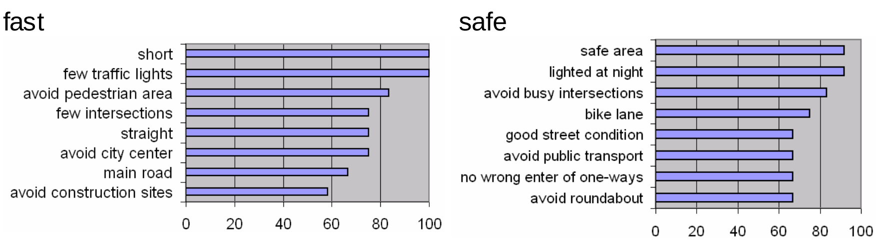


Fig. 2. *Membership structure for the classes "fast" and "safe"*

The result in Fig. 2 is in principle independent from the global importance of a route selection criterion (Table 1) and therefore not bound to any specific wayfinding situation or task. However, the wayfinding task does have a small impact on the found membership structure of a class, as only those criteria which have been mentioned in connection with a given case scenario (see study 1) were presented to the participants of the classification study.

4 Finding the Final Classification

4.1 Guideline

This section presents an informal guideline of how to obtain a single representative classification from a set of classification suggestions, which is demonstrated along with the data from the two previous studies. Whether a suggested class should be kept for the final classification or not depends on several factors.

A major factor is the frequency with that a class has been mentioned in the classification study. Frequently mentioned classes represent intuitive higher-level criteria and should therefore be kept as such in the user interface. According to this rule, the classes “fast”, “safe”, “simple”, and “attractive” are candidates for the final classification (see Fig. 1a). A second factor is the class size where we suggest that classes that comprehend a high number of lower-level attributes should be kept. The third factor concerns the similarity of the final classes: As one of the demands on a good classification of criteria is non-redundancy (Keeny and Raiffa 1993), pairs of criterion classes that share many common attributes should be avoided in the final classification and merged.

4.2 Class size

We define the size of a class C as the ratio between the attribute assignments to C actually made by the participants and the number of theoretically possible assignments to C. A (hypothetical) score of 100% for C thus means that all participants assign all 35 criteria from Table 1 (used as positively and negatively oriented criterion) to C. The class size correlates with the class frequency. Fig. 3 shows the computed size of all 10 mentioned classes. According to the ranking of classes after the class size, again the higher-level attributes “fast”, “safe”, “simple”, and “attractive” should be kept for the final classification.

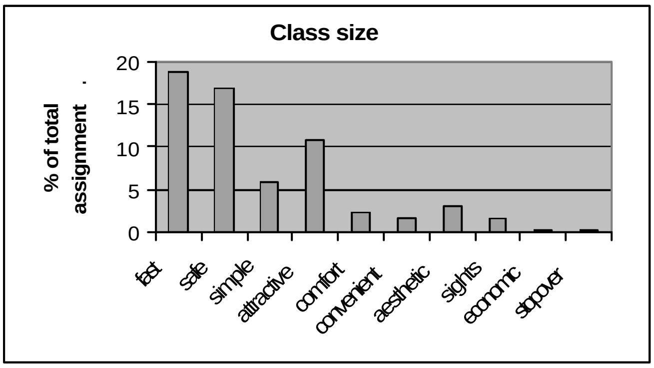


Fig. 3. *Class sizes computed from the number of attribute assignments made to each class*

4.3 Class similarity

We define the similarity of two criterion classes over the presence or absence of assigned criteria in each of these classes, i.e., over binary similarity measures. Due to the fact that participants assigned only a small number of criteria to each class, many zeros appear in the membership tables. Therefore, we use a binary similarity measure that excludes double zeros, i.e., the Tanimoto- (Jaccard-) coefficient (Backhaus et al. 1996). Tversky's ratio model (Tversky 1977) defines a normalized similarity measure between objects as a linear combination of the measures of their common and distinctive features. If setting $\alpha = \beta = 1$ in the ratio model, it defaults to the Tanimoto coefficient.

Fig. 4 shows the lower part of the symmetric similarity matrix containing the Tanimoto coefficient T for each pair-combination within the ten suggested classes. The matrix cells for the most correlated classes are shaded (we use a threshold of $T \geq 0.20$ here).

Ideally, final classes should be independent and not share any attributes. In this case changes in the stated intra-class weightings of one class would not affect the intra-class weightings of another class. Although with partly overlapping classes this will be principally the same, the decision maker needs to mentally separate the effects of changes in the weighting of a lower-level criterion in one class from other higher-level classes that contain the same attribute. Preference statements between uncorrelated higher-level criteria would allow the user for defining precisely the direction of the objective "best route", which is more complex with correlated higher-level criteria.

	fast	safe	sights	comfort	simple	convenient	economic	attractive	aesthetic	stopover
fast	1,00									
safe	0,29	1,00								
sights	0,01	0,04	1,00							
comfort	0,11	0,13	0,14	1,00						
simple	0,16	0,20	0,06	0,09	1,00					
convenient	0,11	0,13	0,05	0,29	0,07	1,00				
economic	0,01	0,00	0,00	0,00	0,00	0,00	1,00			
attractive	0,15	0,23	0,22	0,24	0,11	0,20	0,00	1,00		
aesthetic	0,06	0,08	0,37	0,22	0,05	0,12	0,03	0,35	1,00	
stopover	0,01	0,01	0,03	0,14	0,00	0,15	0,00	0,05	0,07	1,00

Fig. 4. *Similarity matrix showing the Tanimoto coefficient between all suggested classes*

Each of the four preliminary favorite classes ("fast", "safe", "simple", and "attractive") for the final classification, shares a similarity measure ≥ 0.2 with at least one other (Fig. 4). The highest similarity coefficient between favorite classes is found between "fast" and "safe" (0.29), which is partly caused by the fact that the lower-level criteria "parks" (6;7), "avoid heavy traffic" (6;7), or "avoid construction sites" (7;7)—which are altogether not the most characteristic members of both classes (Fig. 2)—have been assigned almost equally often to both classes. Generally, as double zeros are not counted by Tanimoto, not a high number of common attribute assignments, but rather a similar number of assignments increases Tanimoto. However, seen from the aspect of class similarity (Fig. 4), the two classes "fast" and "safe" should merged in the final classification. A strong argument for keeping these two classes separately is that both classes have been mentioned by all respondents (Fig. 1a), and that both classes have a big class size (Fig. 3). Similar considerations concerning class similarity, class size, and class frequency need to be made for the remaining three "favorite" classes. Finally we decide to keep "fast", "safe", "simple", and "attractive" as classes of the final classification.

5 Class Structure

Once a final set of higher-level classes is found, the intra-class importance of class members may be used in combination with a threshold for showing or hiding a route selection criterion in an adaptive user interface. If the user demands simple user interface functionality, preference statements should at least be possible between the higher-level criteria. With the user's increased demand for more detailed intra-class preference statement functionality, the order in which additional class member attributes are shown in the user interface should take into account several impacts, such as global importance (Table 1) or class memberships (Fig. 2). Further it is relevant whether an offered route feature is actually part of one of the route alternatives at hand.

Table 2 shows the result of a suggested function (Eq. 1) that ranks member attributes of the four final higher-level classes according to the two previously mentioned impacts, yet assuming that the attributes are actually found in the choice alternatives at hand. The relevance value r suggests a default intra-class importance measure for a member attribute wrt. to the corresponding higher-level class. The symbol $\underline{r}$ stands for the normalized relevance value.

fast	$\underline{r}$
short	1,00
few traffic lights	0,50
avoid pedestrian area	0,33
few intersections	0,29
avoid heavy traffic	0,26
avoid city center	0,24
straight	0,24
main road	0,20
good street condition	0,14
avoid steep street	0,11

safe	$\underline{r}$
bike lane	1,00
safe area	0,63
lighted at night	0,55
avoid heavy traffic	0,50
good street condition	0,46
avoid busy intersections	0,35
avoid public transport	0,28
no wrong enter of one-ways	0,28
avoid roundabout	0,25
avoid steep street	0,23

simple	$\underline{r}$
good signage	1,00
few intersections	0,39
bike lane	0,36
prominent buildings and LM	0,33
straight	0,32
main road	0,19
short	0,14
avoid roundabout	0,12
lighted at night	0,12
no wrong enter of one-ways	0,11

attractive	$\underline{r}$
sights	1,00
parks	0,77
lakes and rivers	0,58
nice view	0,40
nice bridges	0,37
city center	0,27
good street condition	0,22
snack bar	0,20
avoid tunnel	0,15
prominent buildings and LM	0,15

Table 2. *Normalized relevance values for the ten most relevant members of the four final classes*

$$r_{a,h} = \begin{cases} 0 & \text{if } m_{a,h} = 0 \\ \sqrt[3]{w_a} \cdot \sum_{n=1}^{N} S_{n,h} \cdot m_{a,n}^2 & \text{elsewhere} \end{cases} \qquad \textbf{Eq. 1}$$

where

n $\rightarrow$ number of all classes mentioned in the classification study = N

The computation of the relevance value r for an attribute a with respect to a final higher-level class h considers the global importance of a (ω_a), the grade of membership of the attribute in all suggested classes n ($m_{a,n}$), and the Tanimoto coefficient $T_{n,h}$ between all suggested classes and h ($T_{n,h}$ is part of $S_{n,h}$). For attribute members which have a high degree of membership in eliminated classes only (e.g., the attribute "city center" as member of the eliminated class "aesthetic") the similarity (i.e., the Tanimoto coefficient) between this eliminated class and the final classes needs to be considered. Otherwise the effect of such lower-level attributes would be underestimated in the final classification structure. However, if in the classification study the assigned degree of membership of a in h amounts to zero, we decided to keep this zero value despite any class similarities (first line in Eq. 1).

To avoid double counting of effects that are caused by the same lower-level criterion in several final classes, we introduce $S_{C1,C2}$, which is a modified similarity measure between two classes C_1 and C_2. $S_{C1,C2}$ equals 0 if $C_1 \neq C_2$ and if both C_1 and C_2 are classes of the final classification. Otherwise $S_{C1,C2}$ yields $T_{C1,C2}$. Testing various scaling factors for the impact of ω_a and $m_{a,n}$ lead to the intuitive finding that the impact of ω_a should be reduced as compared to linear weighting (using the cubic root), whereas the impact of $m_{a,n}$ should be increased (using the square). Although the global weights used (Table 1) refer to tourist navigation in urban environments, and the importance weights of criteria may change for a different wayfinding task or a different type of traveler (Bovy and Stern 1990), the distribution of relevance values in each of the final classes will not change dramatically due to the use of the cubic root for ω_a.

The goal of the classification method was to find uncorrelated final classes that share only a small number of overlapping member attributes. Despite this goal, some few attributes, such as "bike lane", appear within the top ten in several final classes (Table 2). This is not problematic, as long as the number of these shared attributes is small so that the user is able to mentally distinguish between the resulting effects on the route, i.e., wrt. the higher level classes, during her preference statements.

6 Conclusions and Future Work

Along with data from two empirical studies, this work presented a method for finding a set of higher-level criteria (factors) that cover the objective of finding a best bicycle route in urban environments. Though referring to this specific domain, we expect that the presented approach can also be applied for the hierarchical structuring of the criterion space of other transportation domains (e.g., car or pedestrian navigation). The work presented an intuitive intra-class ranking of route selection criteria for the final classes by introducing a relevance measure. However, the question of which criteria should actually be shown on the user interface is tricky, as the actual importance of criteria depends also on the range of attribute scores of alternatives at hand and on contextual parameters, such as the user's familiarity with the environment. The assignment of importance weights may even be impossible for the user if no score ranges are known, and it may lead to inconsistencies if too many attributes are presented at the same time to the decision maker (Morris and Jankowski 2000). Requesting the user preferences within an interactive dialogue (Robinson 1990) would have the advantage that the user would need to consider only a small number of criteria at the same time, and that additional criteria presented to the user could be tailored to the results of previous screening phases. That is, unnecessary requests for user preferences that have no effect on the outcome of the route selection algorithm could be avoided (e.g., the request for the importance of bike lanes if there aren't any in the area of interest).

Future work needs to develop context dependent methods that hide irrelevant route selection criteria from the user interface and present only those functionalities that are of interest for the user at the current state of interaction. Hiding or offering route choice criteria is closely connected to the user's preferred sequence of interactive steps and the preferred level of detail in each subsequent step. Whenever a refined query is submitted, the user should be given relevant information about the resulting pre-screened choice alternatives in order to be able to build a conceptual model about existing alternatives and to assign importance weights to each offered criterion. Dynamic updates and continuous feedback (similar as with sensitivity analysis) will give the user the chance to assess the consequences of her changed preference statements and to make her choice under a higher degree of certainty.

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