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Exploring Fuzzy Systems Descriptive Potential for Bikeability Routing

Pablo S. Löw [1], Jukka M. Krisp [1], and Andreas Keler [2]

[1]Applied Geoinformatics, University of Augsburg, Augsburg, Germany
[2]Department of Urban Management, Kyoto University, Kyoto, Japan

Correspondence: Pablo S. Löw (pablo.loew@uni-a.de)

Abstract. This paper proposes a methodology for bicycle route classification using fuzzy logic to facilitate intuitive assessments. As cycling is an essential part of transforming the mobility sector toward sustainability, understanding what makes routes attractive to cyclists is critical.

Traditional routing systems often rely on fixed and abstract measures, but this study explores whether a fuzzy inference system (FIS) can provide more qualitative and intuitive route descriptions. The approach involves calculating multiple routes through a case-study area in Augsburg, Germany, based on distinct weights: length, elevation, and pavement roughness. These routes are compared to those generated by BRouter, a reference routing service.

Results demonstrate that a fuzzy-based method can yield comparable routes and improve route descriptions by offering linguistic attributes. While data inconsistencies in OpenStreetMap (OSM) present challenges, the fuzzy approach provides flexibility in route interpretation. The study highlights the potential for qualitative route descriptions to complement traditional quantitative measures in bicycle navigation systems.

Keywords. Bikeability, Routing, Fuzzy-logic, Accelerometer-data, Python

1 Introduction

Increasing bicycle usage is a key strategy for promoting public health and reducing carbon emissions (Lee et al., 2023). The scientific field of bikeability investigates the push and pull factors influencing cycling adoption (Jonietz and Timpf, 2012; Willberg et al., 2021; Schmid-Querg et al., 2021). However, perceptions of bike-friendly infrastructure vary among individuals, introducing subjectivity into bikeability assessments (Jonietz and Timpf, 2012; Bres et al., 2023).

To address this, we apply fuzzy logic, a mathematical framework for handling uncertainty (Zadeh, 1965; Bellman and Zadeh, 1970; Bezdek, 1993; Novák et al., 1999; Zadeh et al., 2015). Prior research suggests fuzzy logic can also be applied for recommendation purposes (Mamdani and Assilian, 1975; Takagi and Sugeno, 1985; Yager, 2003), making it an interesting tool for improving bicycle route characterization.

This study evaluates its potential by comparing the information available for routes from two different sources in Augsburgs Jakober Vorstadt district. The first set is created with the approach of Löw and Krisp (2024) extended by a route based on total height difference (Yen, 1970). The second set is created with BRouter[1], which is a state of the art bicycle routing software that considers many different factors. Both approaches leverage volunteered geographic information as sources for their data (Goodchild, 1992, 2007; Goodchild and Li, 2012).

2 Data and methodology

BRouter is an implemented routing software that incorporates many bikeability factors (distance, elevation, turns, pavement surface information etc.) to create a complex weight that is not humanly comprehensible. Its factors however are weighted and by adjusting these BRouter can find multiple routes for different bicycles types. The factors and road network are based on OpenStreetMap (OSM) data collected by volunteers except for the elevation. This implies that there is wrong or incomplete information.

We use the data and methodology of Löw and Krisp (2024) that leverages vertical acceleration data collected with smartphones attached to bicycles combined with length as a weight for bicycle friendly routing. Since height difference is generally agreed to be a factor in bikeability (Jonietz and Timpf, 2012; Bres et al., 2023) this approach is ex-

[1]Renner, N. and Contributors https://github.com/nrenner/brouter-web?tab=readme-ov-file

tended by topographical context. Height data is included such that each edge has attributed the net height difference (rise-over-run) that it covers (Boeing, 2024). Because the edges are directed that includes the information up and down. The elevation raster-data has a 1x1 meter resolution and is provided by the Bavarian State Office for Digitalization, Broadband, and Surveying. The road network is also based on OSM data and its quality is comparable to BRouters.

The usage of fuzzy logic in route descriptions is implemented with a system that maps multiple inputs onto output values. Such systems are often referred to as fuzzy inference system and can be structured as follows:

1. Fuzzyfication: In this part a measured crisp value (e.g. length) is related to fuzzy sets via membership functions. These functions model how strong the connection between the input value and each fuzzy set is. The fuzzy sets are named such that they are descriptive (e.g. long).

2. Knowledge Base: The knowledge of each system is represented by the membership functions and the fuzzy "IF-THEN" rules. With these rules the relations of the fuzzy in- and output sets are defined.

3. Interference Engine: The interference is achieved by applying the rules to the fuzzyfied input values. The result of this are fuzzy outputs.

4. Defuzzyfication: This part is optional and only necessary when a fuzzy output set is not fit to act upon. Especially for control systems a crisp value is derived by applying descriptive measure of the fuzzy output set (center of gravity etc.).

The exemplary mamdani style system set up for the characterization of the routes found with our methodology is shown in Fig 1. It is created based on the idea that itself and its results are well understandable. Thus, the rule set contains a minimal number of three rules and all fuzzy sets are implemented as differently skewed triangle functions that sometimes touch or overlap. Triangle functions are easily evaluated and their results do not deviate by a lot from other often used designs (trapezoid, Gaussian). However, the system bears a lot of potential for adjustment and can become more sophisticated. The usage of a fuzzy inference system demands that all values are relative, which is a basic difference between our implementation and BRouter.

3 Comparison of routes and their descriptions

The resulting routes of the two methods are presented in Fig 2. Even though the approaches to finding routes - one with many simple weights versus the other with an adjustable weight - are different the results are comparable.

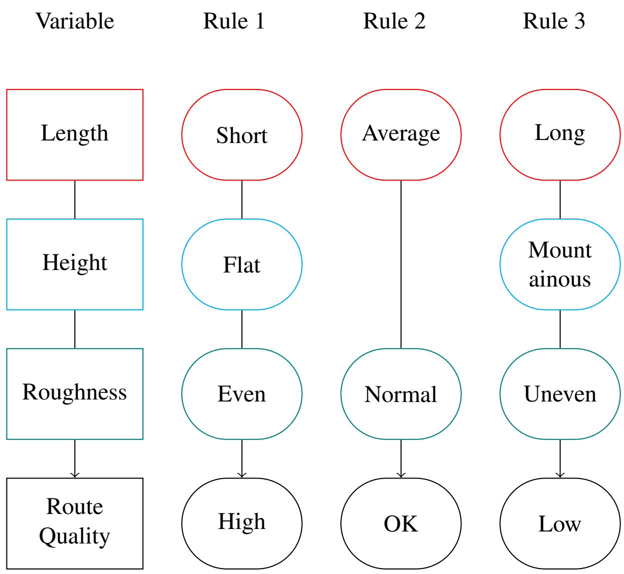

Figure 1. Structure of the Mamdani fuzzy inference system. It consists of three input- and one output variable. Except for Height each features three fuzzy sets that are connected by one of three rules

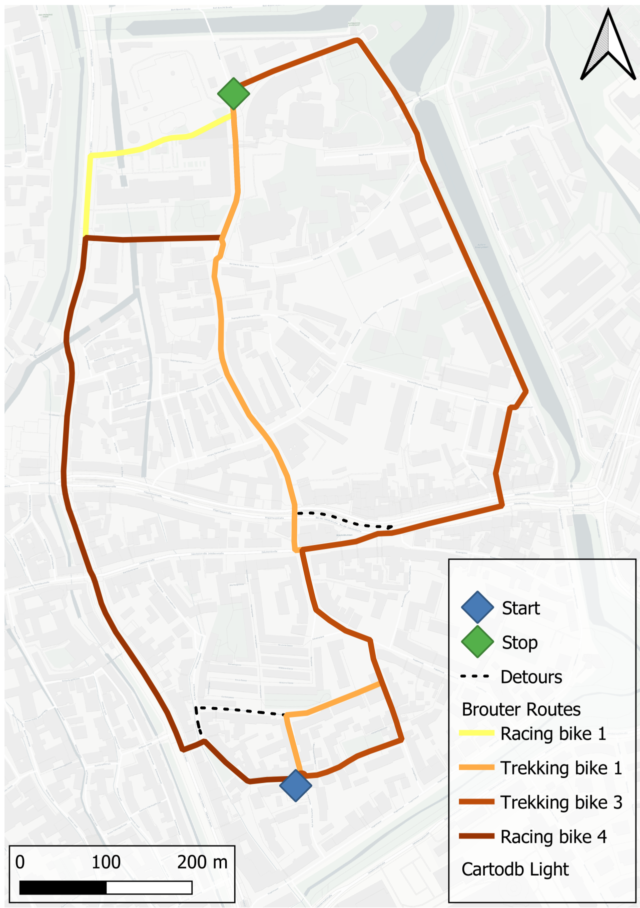

Figure 2. Comparison of the two routing systems. The detours are due to the usage of our custom routing weights

BRouter provides more routes from which some differentiate themselves by minor alterations. Some deviances of our algorithm are due to inaccuracies in the OSM based road network (detour along Trekking bike 1).

Table 1. Route characteristics used by BRouter based on OSM data. Fields with NA mark that the category is not found on a route. *Total* is the total length of the route (categorized + uncategorized). The rows of a column are not summed up because 'Asphalt' can be of 'Excellent', 'Bad' or 'unknown' 'Smoothness'. RB = Racing bike; TR = Trekking bike

BRouter	TB1	RB4	RB1	TB3
Length	[km]	[km]	[km]	[km]
Smoothness				
Bad	0.07	NA	NA	0.07
Excellent	0.05	NA	NA	0.05
Surface				
Asphalt	0.57	0.97	0.93	1.00
Sett	0.40	0.15	0.15	0.40
Total	1.0	1.1	1.1	1.4

Table 2. The results of the fuzzy inference system per route. The top line shows the defuzzyfied route quality. Below are the resulting degrees of the membership functions

Fuzzy System Similar to	Route 1 ≈ TB1	Route 2 = TB3	Route 3 ≈ RB1
Route Quality	0.68	0.17	0.82
Distance			
Short	1.00	-	-
Average	-	-	-
Long	-	1.00	0.55
Height			
Flat	-	1.00	0.80
Mountainous	1.00	-	-
Roughness			
Even	-	0.35	1.00
Normal	-	0.63	-
Uneven	1.00	-	-

BRouter provides information on pavement surface along their routes in meters that is given in Table 1. There is an even more detailed table that gives the weight per network edge, but we argue that for a normal biker it is not necessary. Note that the software only provides one route at a time, which we aggregated into one map and one table to get an overview. Table 1 reveals that BRouter has issues with data availability in the case study region by having fields featuring NA entries. There is a difference between the total length and the cumulative length that is tagged because there are edges with no category.

Table 2 shows the results of the fuzzy inference system. In the first row the relative route quality (defuzzified) is given. The rows below provide information on how the routes do in each of the variables of the fuzzy inference system (fuzzification). Route 2 for example features more normal pavement roughness then even. It can be treated as an explanation or reasoning of the route quality number and could be automatically subsumed into descriptive phrases like:

Route 1 is the second best, because it is short even though it is more mountainous and uneven than the others

3.1 Data and Software Availability

The data and code for the bikeability part are available upon request on the following github repository https://git.rz.uni-augsburg.de/loewpabl/bikeability. It is not openly available, because it incorporates other functionalities and comments that are private or unpublished. The code structured as a python package for creating the fuzzy inference system is openly available at https://git.rz.uni-augsburg.de/loewpabl/fuzzy_polygons under the MIT license.

4 Conclusion

The usage of a fuzzy inference system lends itself to the description of routes in a natural language that might be intuitive to the casual user. This implies that specific information is lost, which can be of interest for advanced bikers. We picked this study area even though the data of OSM on pavement characteristics is not perfect, because the vertical acceleration data is only available here.

The contribution of this paper is a methodology that has to be evaluated by cognitive research on what people prefer. Such an examination is beyond the scope of this paper.

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