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Multi-criteria route planning based on a driver's preferences in multi-criteria route selection

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A B S T R A C T

In this study, some different approaches were designed, implemented, and evaluated to perform multi-criteria route planning by considering a driver's preferences in multi-criteria route selection. At first, by using a designed neuro-fuzzy toolbox, the driver's preferences in multi-criteria route selection such as the preferred criteria in route selection, the number of route-rating classes, and the routes with the same rate were received. Next, to learn the driver's preferences in multi-criteria route selection and to classify any route based on these preferences, a methodology was proposed using a locally linear neuro-fuzzy model (LLNFM) trained with an incremental tree based learning algorithm. In this regard, the proposed LLNFM-based methodology reached better results for running-times, as well as root mean square error (RMSE) estimations in learning and testing processes of training/checking data-set in comparison with those of the proposed adaptive neuro-fuzzy inference system (ANFIS) based methodology. Finally, the trained LLNFM-based methodology was utilized to plan and predict a driver's preferred routes by classifying Pareto-optimal routes obtained by running the modified invasive weed optimization (IWO) algorithm between an origin and a destination of a real urban transportation network based on the driver's preferences in multi-criteria route selection.

1. Introduction

A personalized multi-criteria route planning (PMRP) problem for a driver in a transportation network is known as one of the complicated network analyses (Pahlavani et al., 2012; Nadi and Delavar, 2011). Based on the study done by Papinski and Scott (2011), the routes that are usually selected by the drivers are significantly longer than their shortest routes when the route selection criterion is either 'travel length' or 'travel time'. Accordingly, Papinski and Scott (2011) declared that "... algorithms based on shortest paths to represent routes may not capture real-world route choice decisions." This means that routes computed based on a single criterion shortest route algorithm like Dijkstra may not be desirable for a driver. Also, traffic models and travel patterns that use a single criterion shortest route algorithm are not like the real-world situations (Papinski and Scott, 2011). For example, as Papinski and Scott (2011) described, if the traffic assignment is modeled based on a single criterion shortest route algorithm, the harmful pollutants produced by vehicles will probably be underestimated. In this situation, route planning for a driver based on his/her preferred criteria, i.e., PMRP, can be recognized as a core of a way-finding service in an advanced traveler information system (ATIS). In order to attain such a way-finding service, we organized our current as well as future inquiries as follows.

Before beginning a trip, a driver (as a client) defines his/her destination and selects appropriate criteria via connecting to the specific web server. Then the driver's preferences in multi-criteria route selection are modeled and learned in the server.

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Afterwards, a PMRP algorithm in the server finds routes with the best rate based on the driver's preferences that were learned. These routes are sent to the client/driver's device for both selecting one route and further driving guidance on that route, even before or during the travel. In this regard, we assumed that each client device is a typical modern mobile phone that has a GPS receiver and a data connection to the server via a GPRS network, for example. In traveling to a destination, the client device filters and stores the location and time data obtained from the GPS receiver. Then the data is sent to the server regularly with the driver's-ID and his/her destination. As the server knows the current location of a client, it can ensure that the driver is in the correct selected route. Also, if a dynamic criterion like the time-value of the former selected route by the driver is changed due to unpredictable situations such as vehicle accidents, the server should propose new routes to the driver.

Solving the PMRP as a main goal of this study is categorized as NP-hard problem, as well as one of the branches of multi-criteria optimum routing problems (Mooney and Winstanley, 2006; Gandibleux et al., 2006; Hochmair, 2008; Pahlavani et al., 2006, 2012). Solving the PMRP requires at least two dependent route-selection criteria, which by minimizing the value of a route criterion (e.g., travel time), the others (e.g., travel length value or travel degree of difficulty value) may be maximized. For solving the PMRP, it is not usually recommended to reduce a multi-criteria route planning to a single-criterion route planning by using a weighted linear combination of all edge criteria (Pahlavani et al., 2012; Mooney and Winstanley, 2006). This type of reduction is reported by a few studies like Nadi and Delavar (2011), as well as Sadeghi Niaraki and Kim (2009) that are investigated in Section 2. Pahlavani et al. (2012), Mooney and Winstanley (2006), Corne et al. (2003), and Pereira (2004) stated that reducing a multi-criteria route planning to a single-criterion one is a "radical simplification" of a real-world complex problem, and the multi-criteria route planning does not respond satisfactorily to this type of reduction. Accordingly, solving the PMRP is based on approaches that lead to Pareto-optimal routes (Mooney and Winstanley, 2006; Pahlavani et al., 2012). If solving the PMRP does not consider a driver's preferences in multi-criteria route selection, the driver's choice set will consist of the entire set of Pareto-optimal routes, instead of being reduced to a sub-set of pareto optimal routes that reflect his/her choice criteria. As there are plenty of possible Pareto-optimal routes and based on the advanced traveler information services, it is not recommended to occupy the driver in choosing his/her preferred routes in a travel to a destination (Pahlavani et al., 2012). Hence, for achieving a subset of optimal routes ideal from the driver's point of view, it is possible to create models with the capability of classifying Pareto-optimal routes based on the driver's preferences in multi-criteria route selection. It should be noted that the Pareto-optimal routes have been generated by running multi-objective optimum routing algorithms such as those proposed by Mooney and Winstanley (2006), as well as Pahlavani et al. (2012). Also, all Pareto-optimal routes are considered equally important, i.e., none of them has superiority over the others.

To select a route in the PMRP problem, a driver usually states his/her preferences as some vague and imprecise quantitative values. It seems suitable to use fuzzy logic as one of the modeling approaches in such decision making. Although modeling the driver's knowledge in route selection is possible by such a fuzzy logic system regardless of the precisely quantitative values, there is no standard approach either to convert the driver's knowledge and experience to fuzzy reasoning system rules or to select the optimal number of rules with respect to the driver's preferences in multi-criteria route selection. Also, inconsistencies among rules may occur due to the lack of the driver's knowledge. Therefore, it is only possible to prepare one initial model. Although there are many approaches to find/reduce fuzzy-rules such as those proposed by Yager and Filev (1994), Kosko (1995), and Chiu (1997), it is a difficult task to make a precise adjustment of fuzzy parameters to reduce errors and improve system operation. These are the problems associated with those approaches (e.g., Choi et al., 2008; Henn, 2000) which use only fuzzy systems to model a driver's preference in multi-criteria route selection. In this respect, using artificial neural networks (ANNs) to recognize a driver's preferences by asking the driver directly would be a complementary approach. Moreover, by integrating fuzzy systems and ANNs, information systems can fuse the capabilities of ANNs self-learning with the linguistic expression function of fuzzy inference. Also, there are extensive studies that confirm the possibility of finding/reducing fuzzy-rules from training data by integrating fuzzy systems with ANNs such as those proposed by Dickerson and Kosko (1996), Mitaim and Kosko (2001), Huang and Xing (2002), and Yan (2010).

In this research, some specific approaches were designed, implemented, and evaluated in order to model and learn a driver's preferences in multi-criteria route selection by asking the driver directly via a designed toolbox. The proposed methodology in this study would plan and predict the driver's preferred routes by classifying Pareto-optimal routes between any origin-destination pairs in a transportation network based on the driver's preferences in multi-criteria route selection, which were learned previously. Accordingly, this research featured two main objectives:

1. *Learning a driver's preferences*: In this study, the driver's preferences in multi-criteria route selection were acquired by the driver via the designed toolbox. Then a new approach was proposed to generate a sample of virtual routes that covered the driver's preferences in multi-criteria route selection as a training data-set. In this study, to learn this training data confirmed by the driver, a specific route-classifying methodology was designed, implemented, and evaluated. Accordingly, we proposed two methodologies: (a) the adaptive neuro-fuzzy inference system (ANFIS) trained by the hybrid learning algorithm (Appendix A), and (b) the locally linear neuro-fuzzy model (LLNFM) trained by an incremental tree based learning algorithm (Appendix B). Next, we compared the results obtained by the LLNFM with those obtained by the ANFIS to find a better methodology for classifying any route based on the driver's preferences in multi-criteria route selection. It should be mentioned that both the LLNFM trained by the incremental tree-based learning algorithm and the ANFIS trained by the hybrid learning algorithm provide robust learning capabilities, which have been widely utilized in various applications such as pattern recognition, system identification, and image processing in the last decade (Ying and Pan, 2008; Aliyari Shoorehdeli et al., 2009; Mirmomeni et al., 2006; Gholipour et al., 2007).