Varying salience in indoor landmark selection for familiar and unfamiliar wayfinders: evidence from machine learning and self-reports

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Abstract

For human-centered mobile navigation systems, a computational landmark selection model is critical to automatically include landmarks for communicating routes with users. Although some empirical studies have shown that landmarks selected by familiar and unfamiliar wayfinders, respectively, differ significantly, existing computational models are solely focused on unfamiliar users and ignore selecting landmarks for familiar users, particularly in indoor environments. Meanwhile, it is unclear how the importance of salience metrics employed by machine learning approaches differs from that reported by human participants during landmark selection. In this study, we propose a LambdaMART-based ranking approach to computationally modelling indoor landmark selection. Two models, one for familiar and one for unfamiliar users, respectively, were trained from the human-labelled indoor landmark selection data. The importance of different salience measures in each model was then ranked and compared with human participants' self-report results of a survey. The evaluation results demonstrate that familiarity does indeed matter in the computational modelling of indoor landmark selection. The ranking differences of salience measures in the trained models show that the salience varies with the familiarity of wayfinders. Moreover, the calculated intraclass correlation coefficients (0.62 for familiar, 0.65 for unfamiliar) illustrate the median consistency between the computational results on feature importance and the self-reported importance results by human participants, confirming the reliability and interpretability of the proposed approach.

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1 Introduction

Landmark-based navigation guidance has been widely recognised as an effective way to communicate route information in both outdoor and indoor environments [3, 4]. A lot of

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studies have developed approaches to enable mobile navigation systems to identify suitable landmarks for route instructions automatically. Most of them are based on the formal salience model of landmarks proposed by [10], in which the landmark salience is composed of three dimensions: visual, structural, and semantic. Recently, the personal dimension that refers to individual characteristics (e.g., interaction frequency with landmarks) has also been introduced to model the salience of suitable landmarks [8].

In a route communication context where one person (i.e., the route-giver) attempts to provide route guidance to another (i.e., the route-receiver), she tends to adapt her landmark selection to the route-receiver's individual characteristics to maximise the suitability of the offered landmarks [13]. In particular, the familiarity of wayfinders is a critical individual characteristic to landmark selection. As prior empirical studies found [11], the landmarks selected for familiar and unfamiliar wayfinders are very different, and the semantic salience is highly important in the landmark selection of familiar wayfinders [9].

The research on computational landmark selection mainly focuses on outdoor environments. Computational landmark selection methods for indoor environments remain in the early stage [7, 2, 6]. Most of them are focused on selecting landmarks for guiding unfamiliar users. However, in the real-lifey route communication context, referring to landmarks for guiding people who are partially familiar with environments is common and also critical [14]. It is unknown how the familiarity of users impacts the computational modelling of indoor landmark selection. While some machine learning approaches [5, 6] carry the potential to computationally model landmark selection in both outdoor and indoor environments, little is known about how the importance of salience metrics employed by such machine learning approaches agrees with that reported by human participants during landmark selection.

To address the above-mentioned research gaps, we conducted an experiment to collect indoor landmark selection data for route-receivers who are familiar and unfamiliar with the environment, respectively, and trained LambdaMART-based [1] indoor landmark selection models for users of different familiarity based on the collected data. A familiar-trained-model and an unfamiliar-trained-model were acquired. The dominance of visual, structural, and semantic salience measures was compared based on the gain importance of salience measures in the familiar-trained and unfamiliar-trained computational models. Furthermore, we analysed the dominance consistency of these salience measures between computational results and human participants' self-report results of a survey. It should be noted that this short paper is in parts overlaps with our recently accepted paper [15], to which however it further adds the following contributions:

1. A LambdaMART-based ranking approach is introduced to enable the computational indoor landmark selection to be adaptive to the familiarity of users with environments.
2. The computational results and the human survey results jointly confirm that the importance of salience measures varies with the familiarity of wayfinders.
3. The importance of salience measures from computational results is aligned with human participants' self-reports and quantitatively compared through the intraclass correlation coefficient. The results illustrate the reliability and interpretability of the introduced LambdaMART-based ranking approach in indoor landmark selection.

2 Methods

2.1 Data Collection

A 4-floor, multi-functional university building at the University of Zurich was selected as our study area. 48 participants (24 staff and 24 MSc students) who had worked or studied in the study area at least 18 months were recruited to select indoor landmarks for guiding routes to familiar and unfamiliar wayfinders, respectively. The data collection was mainly composed of pairwise indoor landmark comparison for imaginary familiar wayfinders and unfamiliar wayfinders. After 15 trails of pairwise comparison, the participants were given a multiple choice survey to indicate the important indoor environmental factors that influenced their previous indoor landmarks selections.

2.2 Indoor landmark salience measures

As listed in Table 1, a set of fine-grained quantitative measures are introduced to characterise the visual, structural, and semantic salience of each indoor landmark candidate. For more details about the calculation of indoor landmark salience measures, please refer to [15].

Table 1 Measures of indoor landmark salience.

Salience dimensions	Measures	Symbols	Descriptions
Visual	Colour	vis_col	Hue contrast of indoor landmarks.
	Intensity	vis_its	Brightness of indoor landmarks.
	Shape size	vis_siz	Facade area of indoor landmarks.
Structural	Choice	str_cho	Betweenness centrality in an indoor network.
	Integration	str_itg	Closenss centrality in an indoor network.
	Visibility	str_vbl	Visible area within the horizons.
	Proximity to corridor intersection	str_ci	The distance to the nearest corridor intersection.
	Proximity to floor exits	str_fe	The distance to the nearest floor exits.
	Proximity to building entrance	str_be	The distance to the nearest building entrance.
Semantic	Functional uniqueness	sem_fun	The reciprocal of landmark numbers with the same function.
	Name prominence	sem_nam	The number of items retrieved with the key word of their name in a search engine.
	Semantic relevance	sem_rel	The relevance of of wayfinders' social roles (e.g., student, staff) with functional categories in a search engine.

2.3 LambdaMART-based Indoor Landmark Selection Model

As the nature of landmarks lies in comparison with their surroundings with regard to visual, structural, and semantic characteristics [12, 5], we introduced a machine-learned *ranking* model to computationally model the indoor landmark selection process. Specifically, the state-of-the-art ranking approach, LambdaMART, was used to train indoor landmark selection models for familiar and unfamiliar users, respectively, resulting in one familiar model and one unfamiliar model. The model is formulated as follows:

$$\hat{f}(x) = \hat{f}_M(x) = \sum_{m=1}^{M} f_m(x) \tag{1}$$

where x refers to a set of visual, structural, and semantic salience measures of indoor landmarks. $\hat{f}(x)$ is our landmark suitability score of the trained model $\hat{f}_M(x)$ that is composed of M regression trees, and each regression tree is represented as $f_m(x)$. The model uses a Lambda gradient function as shown in Equation 2 to optimize parameters that minimize the loss of the model in training [1]. Specifically, i is an indoor landmark candidate, and the tuple (i, j) is a partial order representing that i is ranked higher than another landmark candidate j, while (j, i) is in reverse order.

$$\lambda_i = \sum_{(i,j)\in P} \lambda_{ij} - \sum_{(j,i)\in P} \lambda_{ij} \qquad (2)$$

3 Results and Discussion

3.1 Evaluation of models

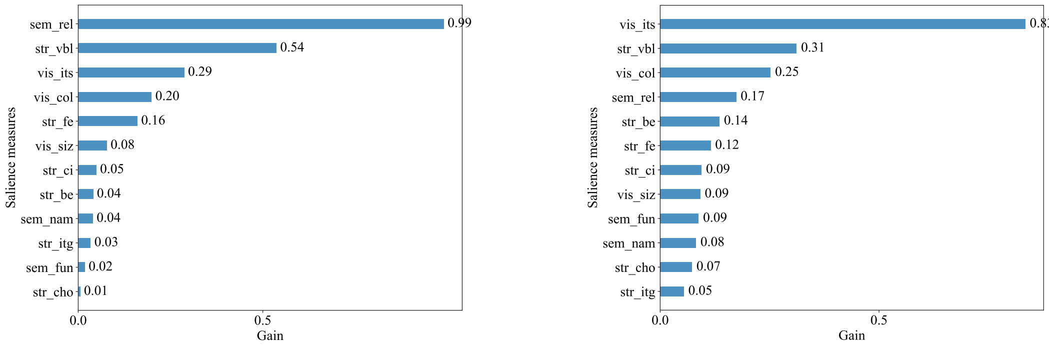
We collected 199 pairs of indoor landmark comparisons for familiar and unfamiliar route-receivers, respectively. We adopted the leave-one-place-out strategy to validate the LambdaMART-based indoor landmark selection models. Consequently, a familiar model and an unfamiliar model were trained, and then both of them were evaluated with the familiar test set and the unfamiliar test set. The hit rate (HR), which refers to the proportion of correctly predicted top-1 items to the total number of predictions [5], was employed to evaluate the performance of trained models. As shown in Table 2, the familiar-trained-model performs better in the familiar test set (HR: 0.74) than in the unfamiliar test set (HR: 0.63). On the contrary, the HR of the unfamiliar-trained-model is higher in the unfamiliar test set (HR: 0.79) than that in the familiar test set (HR: 0.66). Such difference indicates that the familiarity of wayfinders does indeed impact the computational modelling of indoor landmark selection.

Table 2 Hit rates of the familiar-trained-model and the unfamiliar-trained model tested with the familiar and unfamiliar datasets.

Test set	Familiar-trained model	Unfamiliar-trained model
Familiar	0.74	0.66
Unfamiliar	0.63	0.79

3.2 Dominant salience measures from the computational models

In the familiar-trained-model and the unfamiliar-trained-model, the gain of the introduced 12 salience measures was calculated. Figure 1 presents the importance ranking of salience measures in the familiar-trained-model and the unfamiliar-trained-model in descending order. As shown in Figure 1a, the semantic relevance *sem_rel*, which indicates the relatedness of an indoor landmark to users' roles (e.g., staff, students) in buildings, outperforms the other salience measures. It is followed immediately by the other two important salience measures: visibility (*str_vbl*), and intensity (*vis_its*). By contrast, *vis_its* contributes the highest gain to the unfamiliar-trained-model, becoming the most dominant salience measure in selecting indoor landmark for unfamiliar users. The second and third important salience measures are *str_vbl* and colour of indoor landmark (*vis_col*). The difference of dominant salience measures with users' familiarity indicates that mobile indoor navigation systems should give the priority to the semantic relevance of landmarks when selecting landmarks for familiar users, while the visual intensity of landmarks are preferred for unfamiliar users.



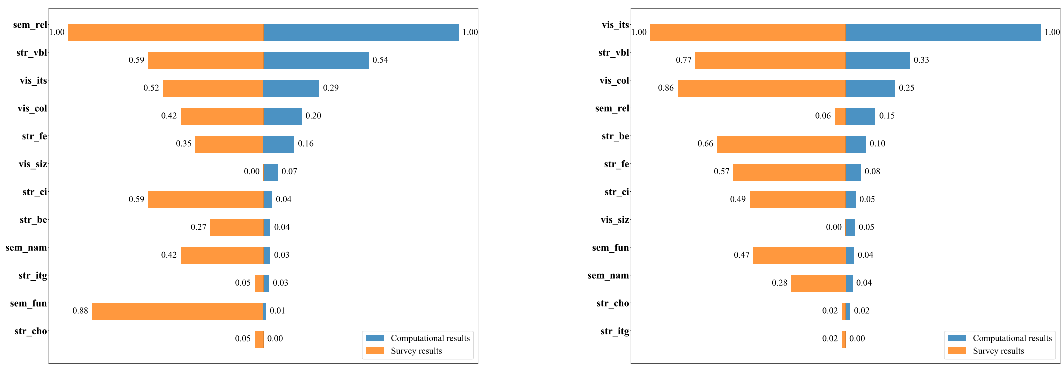
(a) Familiar-trained-model

(b) Unfamiliar-trained-model

Figure 1 Average gain of salience measures in the familiar-trained-model and the unfamiliar-trained-model for indoor landmark selection.

3.3 Comparison with self-report survey results

We mapped the indoor environmental factors that were reported by human participants to have influenced their pairwise comparisons in the survey to the quantitative salience measures (see Table 1) employed in the computational models. Figure 2 shows how the important salience measures employed by the computational models and those self-reported by human participants in the survey differ. Specifically, the survey results were based on the frequency of indoor landmark salience measures voted by participants. The computational results were based on the gain of salience measures in Section 3.2. The data of each group were normalised by min-max feature scaling for fair comparison. Moreover, we calculated the intraclass correlation coefficients (ICC) between them to quantify the consistency between the computational results on feature importance and the self-reported importance results by human participants. As a result, the ICC in the familiar scenario is 0.62 ($p < 0.05$), and that in the unfamiliar scenario is 0.65 ($p < 0.01$). These results demonstrate that the introduced LambadMART-based computational models have a significant median consistency with humans' reported thoughts in indoor landmark selection.



(a) For familiar wayfinders

(b) For unfamiliar wayfinders

Figure 2 Comparison of salience measures between the survey and computational results.

4 Conclusion

In this article, we proposed a LambdaMART-based ranking approach to computationally modelling the indoor landmark selection for familiar and unfamiliar wayfinders. Through the computational results based on human labelled data, the dominant salience measures in indoor landmark selection for wayfinders of different familiarity with the environment were quantified, showing that the semantic relevance predominates over visual and structural dimensions in indoor landmark selection for familiar route-receivers, while the visual intensity is most important for unfamiliar route-receivers. Furthermore, the results show that the feature importance employed by the computational results and the self-reported importance results by human participants are consistent, which confirms the reliability and interpretability of the proposed LambdaMART-based indoor landmark selection models.

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