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Personalized Landmark Sequence Recommendation Method using LSTM-based Network for Navigating in Large Hospitals

Litao Zhu[a,b,c], Jie Shen[a,b,c,*], Georg Gartner[d], Yingxu Hou[c]

[a] *Key Laboratory of Virtual Geographic Environment (Nanjing Normal University), Ministry of Education, Nanjing 210023, China;*

[b] *Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing210023, China;*

[c] *School of Geography Science, Nanjing Normal University, Nanjing 210023, China;*

[d] *Department of Geodesy and Geoinformation, Vienna University of Technology, 1040 Vienna, Austria*

* Corresponding author

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Abstract:

With the development of the Internet and computer technology, research on intelligent hospitals has become a hot topic (Sánchez et al., 2008; Hassan et al., 2019). Context-aware computing (Holzinger et al., 2015), personalized (Hood & Flores, 2012), and navigation (Yoo et al., 2016) are challenges of constructing intelligent hospitals. Hospital is a public space where different people meet for health reasons. Large hospitals are typically complex, and constant updating space and even healthy people may require navigation systems (Hughes et al., 2015). Hospital navigation has unique contextual information due to the high concentration of physical and cognitive problems (e.g., injuries, frailty). Users' wayfinding behavior in hospitals has complex Spatio-temporal sequence patterns. For example, they take the specific medical process at a defined time. Most of the user behaviors are predictable (Song et al., 2010). Location-based behavior is influenced by different factors, such as user preferences (Sun et al., 2020), geographical information (Liu et al., 2020), temporal information (Li et al., 2017; Ying et al., 2017), and sequential information (Feng et al., 2018). Therefore, it is critical to incorporate various types of contextual information to improve the performance of location recommendations.

Landmarks are defined as an entity distinct from its background, which can be used as reference points to describe the positions of nearby spaces and orient (Presson & Montello, 1988). They are entities along a route that can attract the attention of people who are navigating. Previous studies have shown that routes with landmarks are easier for users to acquire route knowledge than routes without these locations (Jansen-Osmann & Fuchs, 2006). Landmarks are useful in complex navigation because they can associate relevant navigational contexts and behavior (Sun et al., 2021). The existing outdoor landmark recommendation methods focus on route recommendation (Zheng et al., 2016) or travel recommendation (Han & Lee, 2015). For hospital environments, landmarks typically contain stairs, escalators, lifts, doors, facilities, etc. And an indoor landmark is a location in indoor space and has contextual information about a specific place, service, facility, or event. Some indoor location recommendation and prediction methods use trajectories to model user behavior and preferences (Zheng et al., 2017; Kim & Lee, 2018; Wang et al., 2019; Claridades & Lee, 2020; Fang et al., 2020). However, few studies of indoor location recommendations focus on the hospital navigation process.

Landmark representation in the navigation has sequence characteristics along with users' behaviors. Early studies explored sequential recommendation methods based on users' behavior, such as matrix factorization (Gao et al., 2015; Ye et al., 2011) and Markov chains (Chen et al., 2014; Cheng et al., 2013). With the advances in deep learning, Recurrent Neural Network (RNN) is used to model sequential behavior, a class of neural networks with recurrent and internal memory units that capture sequential information. Based on RNN, ST-RNN (Liu et al., 2016), Caser (Tang & Wang, 2018), CARA (Manotumruksa et al., 2018), STP-UDGAT (Lim et al., 2020), Deep-Move (Feng et al., 2018) were developed for POI sequence recommendation. In addition, as variants of RNNs, Long Short-Term Memory (LSTM) neural networks are the most widely used to develop a user sequence behavior model. The existing studies adopt the LSTM-based framework for POI sequential recommendation, for example, HST-LSTM (Kong & Wu, 2018), LSTPM (Sun et al., 2020), TMCA (Li et al., 2018), STGN (Zhao et al., 2020), Time-LSTM (Zhu et al., 2017), DRPS (Huang et al., 2019).

Inspired by research on location sequence recommendation models, this study aims to answer the following question: How to model the users' behavior in-hospital navigation for providing a personalized landmark sequence recommendation? Exploring the contextual information for personalized landmark sequence recommendation is the critical issue of navigating in large hospitals. In this study, we conclude that an efficient landmark sequence recommendation requires integrating the following multiple factors. (1) Spatio-Temporal influence: Users go to the next visit based on their location and the current time. (2) User preferences: Different users have different preferences

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in the selection of landmarks. (3) Sequential influence: Patients generally follow the medical treatment process (e.g., taking a number, waiting for a doctor, visiting a doctor, and paying) in the hospital. Fig.1 illustrates the sequence interval between user behaviors.

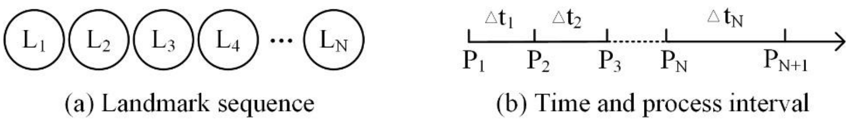

Figure 1. The sequence interval between user behaviors. In (a), L_N refers to the Nth landmark. In (b), P_N refers to the Nth medical process represented, and Δt_N is the time interval between the time when P_N and P_{N+1} are spent.

To address the question mentioned above, we propose a context-aware personalized landmark sequence recommendation model for hospital navigation based on Long Short-Term Memory (LSTM) with an attention mechanism. LSTM model is an encoder-decoder framework. The encoder uses an attention mechanism to represent the contextual information (i.e., Spatio-temporal information, sequential information, and preference). The decoder recommends a personalized landmark sequence to the target user based on contextual information in the navigation system. Finally, we used real indoor Wi-Fi positioning datasets collected in a hospital to evaluate the effectiveness of the proposed method.

To the best of our knowledge, it is the first work to provide the landmark sequence recommendation method for navigation service in large hospitals. This study provides new ideas for constructing intelligent hospitals. It is worth noting that the proposed model is only applicable to complex hospital navigation. The reason can be explained by the fact that the contextual information for hospital navigation is specific. The hospital space has many medical facilities, diverse medical departments, and the specificity of user behavior. In the future, we will do further research work in the following aspects. (1) Refining the personalized landmark sequence recommendation model and contextual information. (2) Applying the proposed model to more complex hospital scenarios to validate the performance of navigation.

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