Novel Method for Enhancing Contents Recommendation Accuracy Using LBS-based Users Viewing Path Similarity

Yoondeuk Seo and Jinho Ahn[1]

Dept. of Comp. Scie., Kyonggi Univ., Iuidong, Yeongtong, Suwon 443-760 Gyeonggi, Republic of Korea

{seoyd, jhahn}@kgu.ac.kr

Abstract

In this paper, we present a novel method for improving contents recommendation accuracy using LBS-based users viewing path similarity. We have previously presented a user similarity-based contents recommendation algorithm using NFC. However, the existing research might not recommend contents related with exhibits which users did not tag but do like because it uses only the information that users tagged the exhibits. Also, it can decrease the quality of service (QoS) because it uses tagging patterns of users that were not interested in the exhibits but tagged them without care and thought. In this paper, to solve these problems of our existing service, we divide an exhibition into the areas through analyzing the wifi signal strength and analyze the areas where the user stays long by using LBS and measure the similarity based on the viewing path between users. By using this analyzed information, the proposed service can recommend contents related with exhibits which are the user`s favorite, but not tagged by the user. Also, it might prevent the degradation of QoS of the existing service because it uses the above mentioned information and the measured similarity.

Keywords: *Ubiquitous Sensor Network, LBS, Museum Viewing, Contents Recommendation*

1. Introduction

The appearance of different technologies such as wireless networks, Internet, Geographical Information Systems (GIS) and Global Positioning Systems (GPS), has introduced a new type of information technology called Location Based Service (LBS) [1-3].

Location Based Service is defined as the ability to locate a mobile user geographically and deliver services to the user based on his or her location. The user can get information such as various types of traffic, weather, shop, and facility, *etc.*, based on the location of the current position through mobile devices such as smart phones in real time. Find friends, driving directions, find the nearest gas stations, Mia Find is a typical case of the LBS. Gartner has selected the LBS as one of the most interesting smart phone applications in 2012 [4].

Due to the growth explosive of the smart phones beginning with iPhone, the LBS is not becoming one of the killer apps with the possibility, but one of the successful killer apps in the market. The success of LBS in smart phones is attributed to the LBS technology support and openness of the platform. It established the foundation for the LBS vitalization in iPhones and Android phones by LBS API, DB, and hardware, such as GPS, WLAN, and digital compass, *etc.* Also, the various LBS services including the foursquare is gathering the success based on this technological support. It is being connected with the other killer apps such as

[1] Corresponding author: Tel.:+82-31-249-9674; Fax:+82-31-249-9673.

social network services (SNS), Augmented Reality (AR), mobile games, providing the various services. In addition, the various types of apps are expected through it in terms of safety and accident prevention [5].

In this paper, we present a novel method for improving contents recommendation accuracy using LBS-based users viewing path similarity. It can recommend appropriately the contents which are appropriate to the user's taste using LBS and the similarity of the users viewing path. We have previously introduced a user similarity-based contents recommendation service that can recommend the contents by similarity of NFC tagging patterns of users [6]. However, the existing research might not recommend contents related with exhibits which users did not tag but do like because it uses only the information that users tagged the exhibits. Also, it can decrease the quality of service (QoS) because it uses tagging patterns of users that were not interested in the exhibits but tagged them without care and thought.

In this paper, to solve these problems of our existing service, we divide an exhibition into the areas through analyzing the Wi-Fi signal strength and analyze the areas where user stays long by using LBS and measure the similarity based on the viewing path between users. By using this analyzed information, the proposed service can recommend contents related with exhibits which are the user`s favorite but not tagged by the user. Also, it might prevent the degradation of QoS of the existing service because it uses the above mentioned information and the measured similarity.

The rest of the paper is organized as follows. Section 2 reviews related works and Section 3 introduces a new similarity-based contents recommend service using LBS. In Sections 4 and 5, we verify superiority of our proposed service mechanism against the previous one and conclude this paper.

2. Related Work

LBS provides wireless users with different applications in the field of vehicle navigation and fleet management, location identification and emergency services. These services are widely recognized as a value added service and due to the diversity of user requirements research efforts are needed to improve the location determination capability and its accuracy and reliability. Recently the mobile device development has mainly concentrated on system integration of GPS, Wi-Fi and cellular wireless networks to cater for different LBS applications. For the integration of all sensor observations, an optimized model is required for optimal estimation of the current user’s location [7-8].

In the area of satellite positioning, a lot of research efforts are put in the development of the new European satellite navigation system Galileo. Having seen the importance of the synergy between navigation services and communication facilities for a wide spectrum of LBS market demand, the navigation and communication integration is in fact one of the architecture requirements in the design of Galileo. Additional data or information from the so-called Local Elements (LE) can be integrated into the Galileo core system through communication networks to improve service performance. Suggested categories of the LE include cellular network positioning, network assisted navigation (Assisted GNSS) and indoor positioning such as Wi-Fi or UWB. This fusion lays a very sound foundation for future development of a high accurate and seamless three dimensional indoor and outdoor positioning systems. Research on establishment of an optimized model and method to accommodate location under complex conditions is of practical significance under such a development trend [9].

For indoor location determination, Wi-Fi positioning techniques based on Wireless Local Area Network (WLAN) or Wireless Personal Area Network (WPAN) are commonly employed nowadays[10-11]. Recent tests have shown that indoor positioning with Wi-Fi systems can generally achieve 1 to 4 m indoor and 10 to 40 m in the outdoor environments [12-13].

Figure 1. Location Determination

As shown in Figure 1, an iPhone provides the location information in order of the GPS satellite signal, Wi-Fi AP and 3G base stations ID according to the error range of the position information of one of the three methods for location determination. An Android phone is the same as well. This location positioning method makes to enable the use of WLAN-based positioning about downtown and indoor which cannot be solved with the GPS-based positioning. As it has become to make database of WLAN AP by operators such as Skyhook, WLAN technology in the current smart phones is becoming the important factor in the 3G/WLAN interworking as well as in the location determination [4].

In Korea, the database construction business and location determination business of WLAN is proceeding and Wi-Fi DB which the mobile telecom company collects will be integrated to the existing LBS information database system. It is expected to be utilized for indoor positioning, safety and accident prevention, *etc*. in the future.

3. Users viewing Path Similarity-based Contents Recommendation Service using LBS

In this paper, the proposed recommendation service is a contents recommendation service using LBS and the similarity of the users viewing path in order to solve the problems due to tagging information that occurs in the existing proposed algorithm.

GPS technology widely used for location tracking has the disadvantage that indoor such as museum is difficult to track because it requires a Line-of-Sight between senders and receivers. Therefore, in this paper, we used the distance measurement method using the Wi-Fi signal strength that is suitable for indoor location tracking [14-15]. As shown in Figure 2, it divides an exhibition into the areas through analyzing the Wi-Fi signal strength and analyzes the areas where user stays long by tracking the position of the user. It extracts the areas that the user stays for more than an average time by analyzing the areas. It calculates the preference weight of the contents based on the extracted area.

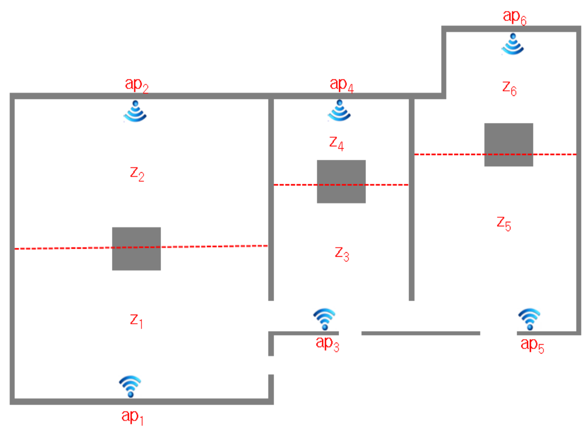

Figure 2. Exhibition Area

The users viewing path similarity-based contents recommendation method recommends contents using path similarity between users. Figure 3 shows the pseudo-code to obtain the similarity on the viewing path of visitors.

```
simPath(User,preUser)
{
   int No = intersection(User.Path, preUser.Path);
   int TotalNo = User.Path.Count;
   pathSim = No/TotalNo;
   return pathSim
}
```

Figure 3. The Similarity on the Viewing Path of Visitors

In Figure 3, *User.Path* represents the set of the viewing path of the current user and *preUser.Path* represents the set of the viewing path of the previous user. It calculates the similarity of the viewing path between two users through dividing the intersection of the two sets by *User.Path.Count* which represents the total number of the viewing path of the current user.

```
simLocation(User,preUser)
{
   int No = intersection(User.LongViewZone, preUser.LongViewZone);
   int TotalNo = User.LongViewZone.Count;
   locationSim = No/TotalNo;
   return locationSim
}
```

Figure 4. The Similarity on the Viewing Area of Visitors

Figure 4 shows the pseudo-code to obtain the similarity on the viewing area of visitors. *User.LongViewZone* represents the set of areas where the current user stays long and *preUser.LongViewZone* represents the set of areas where a previous user stays long. In a similar way to the viewing path similarity, it calculates the similarity of the viewing area between two users through dividing the intersection of two sets by the total number of areas.

Figure 5 shows the pseudo-code to obtain the weighted preference of the similarity about the viewing path between users. The preference weight of the similarity about viewing path between the users based on LBS can be obtained through the sum of the weighted preferences of the similarity about each viewing area, *locationW*, and the weighted preferences of the similarity about each viewing path, *simW*.

```
LocationPathPreference()
{
  for(int i=0;i<Contents.Count;i++)
  {
    if(contents[i] ∈ Path)
    {
      contents[i].weight = k * contents[i].weight + contents[i].weight;
    }
    if(contents[i] ∈ LongViewZone)
    {
      contents[i].weight = k * contents[i].weight + contents[i].weight;
    }
  }
  for(int i=0;i<Contents.Count;i++)
  {
    for(int j=0; j<preUser.Count; j++)
    {
      if(simPath(User,preUser[j])>0.7)
      {
        if(contents[i] ∈ preUser[j].BL)
        {
          simweight = simPath(User, preUser[j]);
          contents[i].simW = contents[i].weight * simweight + contents[i].simW;
        }
      }
      if(simLocation(User,preUser[j])>0.7)
      {
        if(contents[i] ∈ preUser[j].BL)
        {
          simweight = simLocation(User, preUser[j]);
          contents[i].locationW = contents[i].weight * simweight + contents[i].locationW;
        }
      }
    }
    contents[i].Preference = contents[i].simW + contents[i].locationW;
  }
}
```

Figure 5. The Weighted Preference of the Similarity about the Viewing Path between Users

In order to prevent the contents which are the user`s favorite but not tagged by the user from not being recommended, it adjusts the weight by using the user viewing path. *Path.Count* represents the total number of exhibits in the viewing path of the user. It adjusts the weights, *contents[i].Weight*, for the contents associated with the exhibits on display in the exhibition that exist in the user viewing path, *Path.contents[i]*. In addition, in order to prevent the degradation of QoS due to curiosity patterns, it uses the exhibition information that the user stays long. *LongViewZone* represents a set of areas where the user stays long. It adjusts the weights about contents associated with the exhibits on display in the exhibition that exist in the *LongViewZone*.

It calculates the weighted preference of the similarity of the viewing path, *simW*, and the weighted preference of similarity of the viewing area, *locationW*, about all contents by the adjusted weights.

If there exists any contents, *i*, in the shopping list, *preUser[j].BL*, it calculates the weighted preference of similarity of the viewing path about contents *i*, *contents[i].simW*, using the weight of contents, *contents[i].weight*, and *simPath(User, preUser[j])*.

In a similar way to *simW*, it calculates the weighted preference of the similarity of the viewing area, *contents[i].locationW*, about contents *i*.

The threshold defines 0.7, meaning very strong relation by Pearson correlation coefficient because the users having the similarity more than the specific value can be seen to have the similar tastes [16].

4. Performance Evaluation

In this section, we can show how effectively the proposed service can recommend visitors their favorite contents. Our experimental environment is in Table 1.

Table 1. Experimental Environment

Parameter	Value
No. of Exhibition Rooms	10
No. of Area	30
No. of Exhibits	30
No. of Contents	60
No. of Previous Visitors	100

Experiments will be performed in two different ways. The one is the prior preferences of all contents are assumed to be the same. The other is the prior preferences of all contents are assumed to be different depending on the exhibits.

We assume that the number of exhibition rooms is ten and each room has three areas. So, there are a total of 30 areas. Each room has three exhibits. So, there are a total of 30 exhibits. Each exhibits has two related contents. So, the total number of contents is 60. The number of previous visitors is 100. We assume that previous visitors watch at least three exhibitions, tags at least five exhibits, and purchase at least five contents.

In order to evaluate the proposed method, we set up three users. The first user has watched rooms 1, 2, 6, 7 and 9 and tagged exhibits 2, 3, 17, 18 and 27 and stays long at areas 1, 4, 16, 18 and 27. His or her favorite contents would be 2, 8, 31, 35 and 53. The second user has watched rooms 2, 3, 6, 7 and 10 and tagged exhibits 4, 9, 17, 20 and 28 and stays long at areas 4, 7, 17, 19 and 28. His or her favorite contents would be 7, 14, 34, 38 and 56. The last user has watched rooms 1, 3, 5, 8 and 9 and tagged exhibits 3, 7, 14, 24 and 25 and stays long at areas 3, 8, 15, 24 and 25. His or her favorite contents would be 6, 16, 30, 48 and 50.

Experiments are performed to find out how the preference values for the present user are changed depending on which services are applied, that is, tagging patterns similarity-based method and proposed method. Additionally, we can find out how many differences occur between these services to contents based on the user preference.

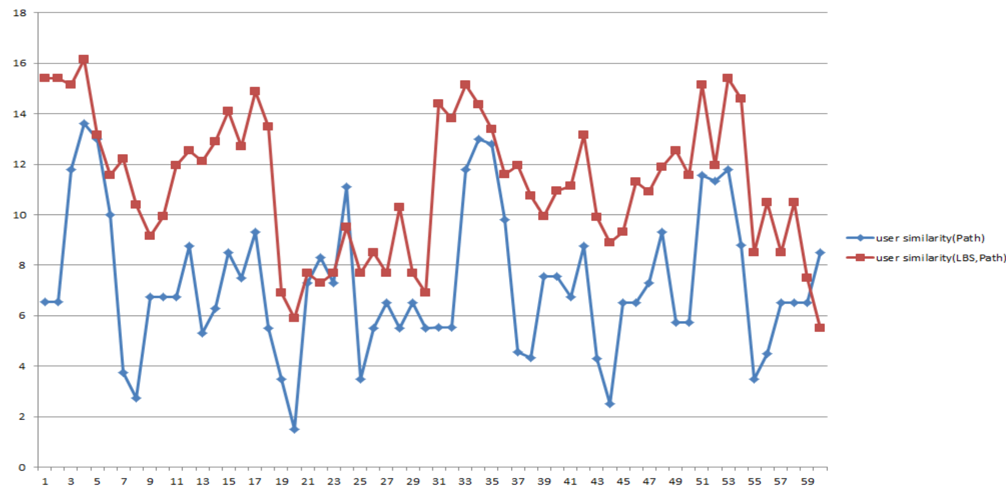

Figure 6. User A

In the first experiment, Figure 6 shows that each method is applied about the first user. The contents 2, 8 and 31 which did not tagged have low preference values in the tagging pattern similarity-based methods, but high preference values in the proposed method.

In the second experiment, Figure 7 shows that each method is applied about second user. In this case, the two methods almost seems to follow a similar pattern. But we can see that the proposed method recommends a bit more strongly than the tagging pattern similarity-based method in the case of contents 38 which is suitable for the user’s taste.

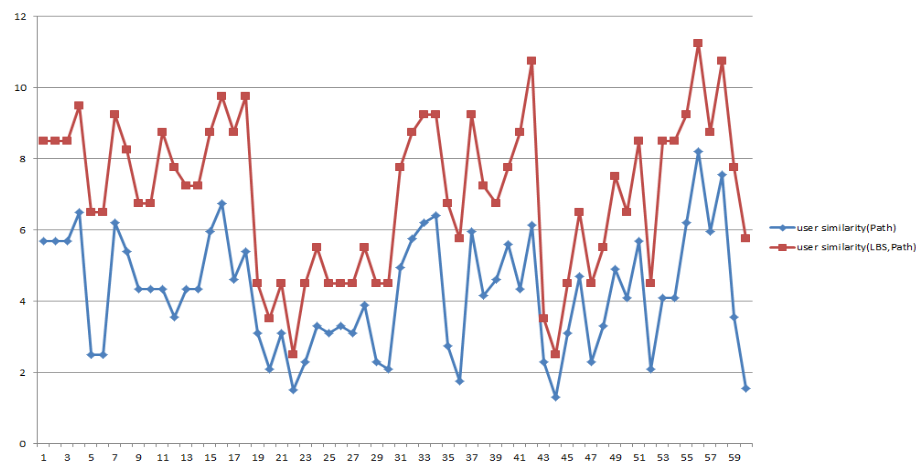

Figure 7. User B

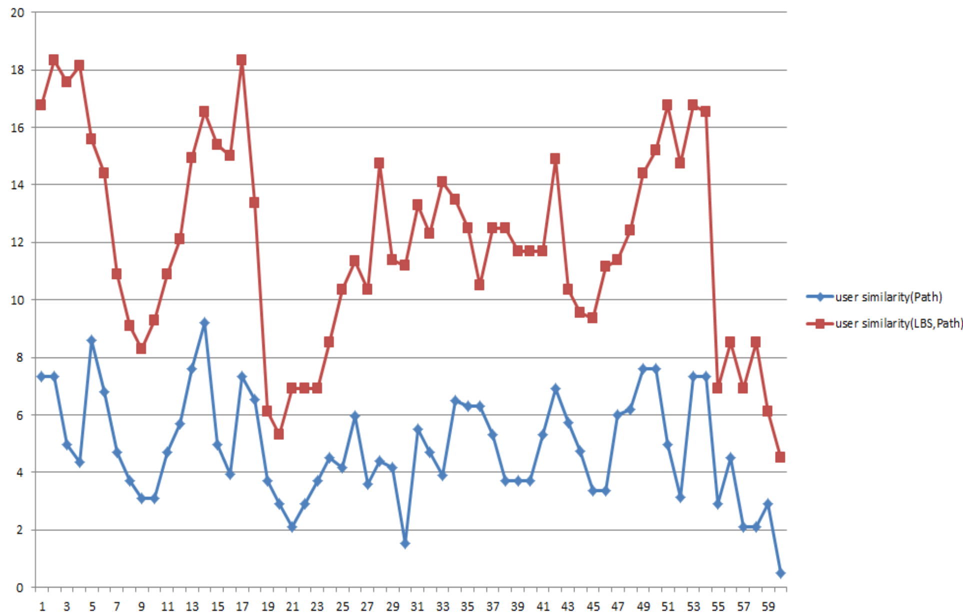

Figure 8. User C

In the third experiment, Figure 8 shows that each method is applied about the third user. The contents 16 and 30 which are suitable for the user's taste seems to have low preference values in the tagging pattern similarity-based method, but high preference values in the proposed method.

Throughout the experiments, the tagging pattern similarity-based method recommends an appropriate contents, but in the case of some users, it has some critical problems that it may not recommend contents related with exhibits which some users like better, but haven't tagged. But we can see that the proposed method recommends users' favorite contents which users have not tagged. Therefore, the proposed method can help users to actually find the favorite contents and improve users satisfaction by recommending contents that fit the user's taste.

5. Conclusions

In this paper, we proposed a user viewing path similarity-based contents recommendation method using LBS to improve the counterpart of our previously developed museum viewing system. The proposed method divides an exhibition into the areas through analyzing the Wi-Fi signal strength and analyzes the areas where the user stays long by using LBS and measures the similarity based on the viewing path between users. By using this analyzed information, the proposed service can recommend contents related with exhibits which are the user`s favorite but not tagged by the user. Also, it might prevent the degradation of QoS of the existing service because it uses the above mentioned information and the measured similarity.

Acknowledgements

This research was supported by Kyonggi University Research Grant 2012.

References

[1] S. Steiniger, M. Neun and A. Edwardes, “Foundations of Location Based Services”, Lecture Notes on LBS, Department of Geography, University of Zurich, **(2006)**.
[2] B. S. Karlsen, “Enabling a Ubiquitous Location Based Service on Campus”, Master Thesis, Norwegian University of Science and Technology, **(2006)**.
[3] T. Reshma, P. Sundara Kumar, M. J. Ratna Kanth Babu and K. Sundara Kumar, “Simulation of Runoff in Watersheds using SCS-CN and MUSKINGUM-CUNGE METHODS using Remote Sensing and Geographical Information Systems”, International Journal of Advanced Science and Technology, vol. 25, no. 31, **(2010)**.
[4] Gartner Identifies the Top 10 Consumer Mobile Applications for 2012, http://www.gartner.com/it/page.jsp?id=1230413.
[5] G. M. Jung and A. S. Choi, “Smart-Phone based LBS Technology Trend Analysis”, TTA Journal, vol. 33, **(2010)**.
[6] Y. D. Seo and J. H. Ahn, “Reliable Contents Recommendation Service Based On Similarity Of Users Tagging”, Proceedings of the second International Conference on Conference On Computers, Networks, Systems, and Industrial Engineering(CNSI2012), Jeju, Korea, **(2012)** July, pp. 474-479.
[7] L. Xia, E. Mok and G. Xue, “Optimized Hybrid Location Service for Supply Chain”, Proceedings of the International Workshop on Successful Strategies in Supply Chain Management, Hong Kong, **(2006)** January, pp. 309-316.
[8] E. Mok and L. Xia, “Hybrid GPS and Wireless System for Geolocation Positioning in Urban Canyons”, Proceedings of the International Workshop on Successful Strategies in Supply Chain Management, Hong Kong, **(2006)** January, pp. 221-233.
[9] C. Pen, G. Junzhong, L. Xin and T. Rong, “A Probabilistic Approach for GNN Queries in LBS”, International Journal of Multimedia and Ubiquitous Engineering, vol. 7, no. 2, **(2012)**.
[10] G. D. Kang, T. Pérennou and M. Diaz, “Barycentric Location Estimation for Wireless Network Indoors Localization”, International Journal of Hybrid Information Technology, vol. 2, no. 2, **(2009)**.
[11] Y. Jaegeol, J. Jaehun and L. Gyeyoung, “Petri Net-Based Ontology Analysis Method for Indoor Location-Based Service System”, International Journal of Advanced Science and Technology, vol. 39, no. 75, **(2012)**.
[12] Y. C. Cheng and Y. Chawathe, “Accuracy Characterization for Metropolitan-scale Wi-Fi Localization”, Intel Research, **(2005)** January.
[13] G. Retscher, E. Moser, D. Vredeveld, D. Heberling and J. Pamp, “Performance and Accuracy Test of a WiFi Indoor Positioning System”, Journal of Applied Geodesy, vol. 1, no. 2, **(2007)**.
[14] J. G. Yim, J. H. Joo and S. H. Jeong, “Wireless LAN-Based User Tracking Method and Experiment for Location-Based Services”, Journal of Society for e-Business Studies, vol. 13, no. 4, **(2008)**.
[15] D. Y. Kim, D. S. Seong and K. B. Lee, “Implementation of an efficient multipoint sight-seeing guidance system based on LBS”, Journal of Kor. Inst. of Info. Tech., vol. 9, no. 1, **(2011)**.
[16] P. Ahlgren, B. Jarneving and R. Rousseau, “Requirements for a cocitation similarity measure with special reference to Pearson’s correlation coefficient”, Journal of the American Society for Information Science and Technology, vol. 54, no. 6, **(2003)**.

Authors

Yoon-Deuk Seo received his B.S. and M.S. degrees in Computer Science from Kyonggi University, Korea, in 2008 and 2010, respectively. He has been a Ph.D. student in Department of Computer Science, Kyonggi University from 2010. His research interests include distributed computing, RFID systems, P2P networks and group communication.

Jinho Ahn received his B.S., M.S. and Ph.D. degrees in Computer Science and Engineering from Korea University, Korea, in 1997, 1999 and 2003, respectively. He has been an associate professor in Department of Computer Science, Kyonggi University. He has published more than 70 papers in refereed journals and conference proceedings and served as program or organizing committee member or session chair in several domestic/international conferences and editor-in-chief of journal of Korean Institute of Information Technology and editorial board member of journal of Korean Society for Internet Information. His research interests include distributed computing, fault-tolerance, sensor networks and mobile agent systems.