FOOD TOUR RECOMMENDATION USING MODIFIED ANT COLONY ALGORITHM

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ABSTRACT. Food tour is popular and becomes one of the most dynamic and creative segments of tourism. Popular itinerary of food tour can be extracted from the information in the Internet, but preference of the user must also be taken into consideration. This paper proposed a modified Ant Colony algorithm to find best possible itineraries through approximation and heuristic method by taking majority preferences of users into account when computing the recommended itinerary. The experiments were conducted on a food tour of restaurants in Yaowarat, a Bangkok's China-town of Thailand. The results show that our proposed algorithm can recommend itineraries with rank-accuracy 0.88-0.97, which is better than the original Ant Colony algorithm with rank-accuracy 0.61-0.63.

Keywords: food tour, recommendation system, ant colony, tourism

INTRODUCTION

Internet has become the leader information source for travelling (Xiang, 2014). The human behavior has rapidly changed from using printed materials like guide books and travel documents to be online resources like travellers' reviews, forums and blog posts since they provide more updated and interactive information than the offline ones. Moreover, connectivity power of social media and spontaneous volunteerism of individuals is stimulating the generation of quality information in digital society. Crowdsourcing is a promising approach to make the travellers achieve recent travel information and useful experiences (Alam, 2012). Assuming that we are a traveller and want to plan our trip, we may start by searching the information on the Internet and sometimes post our travelling information online to ask for confirmation and details from other Internet users who might have more recent experience on particular destination than us. However, we may suspect the precision of information provided by some users, but it can be trustable if many users confirm on those information.

Food tour is a popular travellers' activity for experiencing local life in a town with variety of food. In recent years, food tour has grown considerably and has become one of the most dynamic and creative segments of tourism (World Tourism Organization, 2012). Both destinations and tourism companies are aware of the importance of food tour in order to diversify tourism and stimulate local, regional and national economic development. Furthermore, food tour includes in its discourse ethical and sustainable values based on the territory, the landscape, the sea, local culture, local products, authenticity, which is something it has in common with current trends of cultural consumption. For many of the world's tourists, returning to familiar destinations to enjoy, try and test recipes, or traveling further afield in search of a new and special cuisine, food tour has become a central part of the tourism experience.

Tour planning problem has been widely studied in previous works (Zhou, 2009; Huang, 2013; Sombatsricharoen, 2015). From their point of views, this problem is an optimization of travelling salesman problem: TSP (Lawler, 1985) under constraints such as time, costs and popularity of places. However, there are two approaches of research in this area, i.e., 1) developing algorithmic solutions to find best itineraries through approximation and heuristics and 2) learning from human behaviors and customize itineraries for them (Yahi, 2015). However, when the travellers plan for the trip, they prefer to combine both popular itineraries and their preferences for developing their own itinerary. Therefore, this paper focuses to hybrid those two approaches by proposing an algorithm that finds best possible itineraries through approximation and heuristic method and taking majority preferences of users into account when computing the recommended itinerary. In the aspect of food tour, the preference factors can be anything such as favor, new cuisine, convenience of access, mealtime etc.

Although several optimization algorithms can be used to solve this TSP problem e.g., genetic algorithms, simulated annealing, Tabu search, river formation dynamics, cross entropy method, the problem of food tour recommendation is slightly different. The key problem is current information of travellers' popularity must be taken into account. This can be handled by Ant Colony system where each traveller information is similar to an ant moving in the colony, leaving pheromones, and dynamic change over the time. Then, it is suitable for solving this problem using Ant Colony optimization as stated in (Zhou, 2009; Huang, 2013). However, differ from parameter proposed in (Sombatsricharoen, 2015), new parameter which represents individual preference and is adapted in each iteration is presented in this work. This parameter is also used during the process of selecting route of AC. Retrieved itineraries are ranked based not only on distance between point of interests but also preferences that makes users feel much more satisfactory. Yaowarat, a Bangkok's Chinatown in Thailand, is selected for studying about food tasting planning since it is popular among tourist attractions.

ANT COLONY AND MODIFIED ANT COLONY

The Ant Colony (AC) was first introduced in (Dorigo, 1991) to solve complexity of discrete combinatorial optimization problems. The algorithm was inspired by the behaviors of real ants. When exploring a region, ants are able to find the shortest path between their nest and a food source. An ant leaves some pheromone at the amount of τ on the ground when it travels and marks the path by a trail of this substance. The pheromone would evaporate at a certain rate ρ as time goes by. The next ant will smell the remained pheromone on different routes and chooses one with probability proportional to the amount of pheromone. The ant that follows the path will leave its own pheromone. Based on pheromone intensity, ants progressively construct their tours. Finally, ants can find the shortest path between source and destination as time goes by. Therefore AC is also applied to solve TSP (Dorigo, 1997). The main parameters that are used to build up the system are α, β, ρ and Q. The parameter α and β control the relative importance of pheromone trail and distance between the cities in TSP, respectively, ρ refers to the rate of pheromone evaporation, and Q is the constant value.

Food tour recommendation can be mapped into TSP. By modeling restaurants as cities, ant colony is exploited to find the optimized route between the restaurants. where an ant visits each restaurant once and needs not to return to the first restaurant. However, the **original AC** considers the route selection according to two factors, i.e., the pheromone τ_{ij} between restaurant *i* and *j*, and heuristic information η_{ij} of ant's moving from restaurant i and j. Heuristic information is defined as $\eta_{ij} = 1/d_{ij}$ where d_{ij} is the distance between restaurant i and j. The transition probability of an ant *k* moving from restaurant i to j, p_{ij}^k, is defined as in Eq. (1).

$$p_{ij}^k = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta}}{\sum_{r \in Table_k} (\tau_{ir}^{\alpha} \times \eta_{ir}^{\beta})}, & if\ j \in Table_k \\ 0 \quad , & otherwise \end{cases} \tag{4}$$

$Table_k$ is a set of candidate restaurants in which an ant k can visit in the next step, this set is dynamically changed in each movement of ant k .Assuming there are m ants in the colony, the pheromone τ_{ij} will evaporate as time goes by, and the evaporation rate is denoted as ρ , where $(1-\rho)$ represents the evaporation of trail. The pheromone update formula is shown in Eq. (2).

$$\tau_{ij} = (1-\rho).\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{2}$$

Note that $\Delta\tau_{ij}^k = Q / L_k$ is the quantity per unit of length of trail substance laid on edge (i, j) when ant k moves from restaurant i to j .

In practice, the factors for moving between restaurants are not limited to only pheromone and distance. Assuming an ant as human, s/he may select to visit the restaurants based not only on the distance but also their preference. Therefore, a **modified AC** is presented with a new transition probability of an ant k moving from restaurant i to j , $\hat{p}_{ij}^k$, as shown in Eq. (3).

$$\hat{p}_{ij}^k = \begin{cases} \dfrac{\tau_{ij}^{\alpha} \times \eta_{ij}^{\beta} \times \bar{w}_{ij}}{\sum_{r \in Table_k} (\tau_{ir}^{\alpha} \times \eta_{ir}^{\beta} \times \bar{w}_{ij})}, & if\ j \in Table_k \\ 0 \quad , & otherwise \end{cases} \tag{3}$$

A new parameter $\bar{w}_{ij}$ is presented to take the route preferences into consideration when moving from restaurant i to j . It is the average weight among multiple route preferences. The $\bar{w}_{ij}$ is equal to one when all ants prefer such route while becomes zero when all ants do not prefer such route. Furthermore, the pheromone update formula is modified as in Eq. (4)

$$\hat{\tau}_{ij} = (1-\rho)(\hat{\tau}_{ij}) + \sum_{k=1}^{m} \Delta p_{ij}^k \text{ ,where } \Delta p_{ij}^k = \frac{Q}{L_k} \times \bar{w}_{ij}^k \tag{4}$$

Although pheromone update formula is modified, ant can still walk on the particular route but it may not prefer to do so. Majority of ants will guide them which route they should go but it depends on the preference of each ant in making a decision.

EVALUATION

The objective in building food tour recommendation system is to assist travellers by recommending the tour itineraries with regard to their preferences and popular preferences from majority of people. Therefore, the evaluation focuses on the accuracy of retrieving desired itinerary based on majority preferences to the users. The experiments compare the ranked-recommended itineraries retrieved from original AC and modified AC. The original AC ranks the recommended itineraries based on distance between restaurants in the itinerary while our modified AC takes both distances and users' preferences into consideration and ranks the recommended itineraries based on majority preferences. In this work, the case study is Yaowarat, a Bangkok's China town in Thailand, since it is famous on food tour for travellers staying or visiting Thailand. In total, 53 famous restaurants (both in building and side-street) in such area that serve meal and/or dessert are selected. Google Maps API is employed to find the geo-location of each restaurant and distance between them. There are various preferences for food tasting, e.g., some people prefer particular route between two restaurants but not a short distance, some people prefer meat-dish restaurant before dessert restaurant, some people prefer particular restaurant since it provides a new cuisine, etc. From a preliminary survey, the average number of restaurants per meal of traveller is three different restaurants. This can generate four scenarios with different numbers of meat-dish and dessert-dish restaurants as in Table 1.

Table 1. Scenarios for Evaluation

Scenario	Number of meat-dish restaurants	Number of dessert-dish restaurants
1	3	0
2	2	1
3	1	2
4	0	3

In this study, 50 volunteers were selected as focus group. The first inclusion criterion for a volunteer to participate is that s/he must visited Yaowarat at least once. Each user was asked to select the known restaurants in Yaowarat area. According to the each scenario, the combination and sequence of known restaurants of such user are then generated as food tasting itineraries. The user was asked again to give a rank value to each itinerary according to their preference. The rank value is then adjusted to be a weight within a range between 0 and 1 where weight 1 means the highest preference. These values will be used to calculate the transition probability and pheromone update as in Eq. (3) and (4), respectively. For example, user's choices of restaurant based on scenario 2 are Singapore Pochana: A (meat-dish); Texas Suki: B (meat-dish) and Burapa Bird's Nest: C (dessert-dish). These three restaurants can generate six different itineraries, i.e. A→B→C, A→C→B, B→A→C, B→C→A, C→A→B, and C→B→A. Then, the user will be asked to rank these itineraries based on preference. Since the preferences among different users are broad, users are then clustered based on their preferences using Fleiss' Kappa (Landis, 1997), an inter-rater agreement with multiple raters, for grouping those with high agreements into the groups of 10, 20, 30 and 40 (a user can be a member of more than one group). The agreements of each group for each scenario are shown in Table 2. Note that the agreement is likely to decrease when the number of users increases. The ranked itineraries from users is considered as correct answers for evaluating the recommended food tasting itinerary from both original AC and modified AC algorithms.

Table 2. Fleiss' Kappa Agreement of Group for each Scenario

Group of users	Scenario 1	Scenario 2	Scenario 3	Scenario 4
10	0.653	0.529	0.711	0.578
20	0.297	0.395	0.417	0.297
30	0.151	0.294	0.247	0.175
40	0.074	0.206	0.145	0.096

The main objective of evaluation is to examine the hypothesis that modified AC would provide the recommended itineraries that match majority users' desire more than original AC. The rank-accuracy (Richardson, 2013) is employed as measurement. Top N itineraries retrieved from different algorithms and scenarios are evaluated. Here, N is varied from 1 to 5.

RESULTS

Table 3 shows the average rank-accuracies from Top 1 to Top 5 of retrieved itineraries in each algorithm. Overall results show that modified AC is better than original AC for all groups of users and all scenarios. The average rank-accuracies of original AC is between 0.61 and 0.63 while the average rank-accuracies of modified AC is between 0.88 and 0.97. The differences of rank-accuracy between two algorithms are significant in every group of users with 95% confidence interval. However, the average rank-accuracy tends to be decreasing when the number of users increases for both algorithms as shown in Figure 1. This is obviously since the agreement for the group with larger number of users is lower than the agreement of those with smaller number of users. Modified AC performs best on scenario 3, i.e., 1 meat-dish and 2 dessert-dish restaurants. This scenario is the most popular for travellers. Note that the following optimized parameter values were used in this experiment: maximum number of iteration = 10^3, number of ants = number of restaurants * 2, $a=1$, $b=5$, $r=0.7$ and $Q=1$.

Table 3. Average Rank-Accuracy of original AC and modified AC

Group of users	Algorithms	Average Rank-Accuracies from Top 1 to Top 5				Average	S.D.
		Scenario1	Average	Scenario3	Scenario4		
10	Original AC	0.67	0.67	0.47	0.60	0.61	0.0943
	Modified AC	0.93	1.00	1.00	0.93	0.97	0.0404
20	Original AC	0.67	0.67	0.47	0.67	0.62	0.1000
	Modified AC	0.80	0.93	1.00	0.87	0.90	0.0852
30	Original AC	0.60	0.67	0.47	0.67	0.61	0.0943
	Modified AC	0.80	0.93	1.00	0.80	0.88	0.0995
40	Original AC	0.67	0.67	0.53	0.67	0.63	0.0700
	Modified AC	0.80	0.93	1.00	0.80	0.88	0.0995

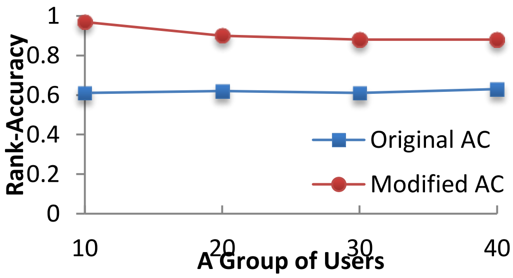

Figure 1. Trends of Rank-Accuracy for different sizes of group of users

DISCUSSION

The results give us several remarkable notices. First, a large number of users who provide their preferences can make the value of agreement among them becomes low and may affect to low rank-accuracy. In other words, the level of agreement among users highly affects the rank-accuracy. Second, by taking majority preferences into consideration, this extends the recommendation system to retrieve much more desired itinerary based on users' preference than just only consider the shortest distance between the restaurants. The preference of users can be anything such as preference to eat meat dishes before dessert, some restaurants are currently popular, particular sequences of visiting restaurants in the itinerary are famous, etc. This information can be captured easily by monitoring the activity log when users use the system, and feeding back to the modified AC for adjusting their ranking methodology in a real-time manner. Furthermore, there might be other factors that may not be addressed yet in this work such as opening and closing time of the restaurants, availability time of the travellers, must-eat restaurants, or which mealtime are they seeking for itinerary. These will be studied in the future work.

CONCLUSION

This work proposed modified Ant Colony algorithm that takes both distances and users' preferences into account and ranks the recommended itineraries based on majority preferences. This food tour recommendation system assists travellers by recommending the tour itineraries with regard to their preferences and popular preferences from majority of people. The evaluation was performed on 50 volunteers in raking their preferred itineraries based on different scenario for food tour in Yaowarat area. The algorithmic solutions from the proposed modified Ant Colony algorithm can help to retrieve preferred itineraries better than the original Ant Colony algorithm.

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