A Support System for Healthy Eating Habits: Optimization of Recipe Retrieval

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Abstract. In this paper, we propose a support system for healthy eating habits. Current methods of recipe retrieval generally rely on keywords or popularity. However, such approaches offer the same results to different users. In order to resolve this issue, we have developed a support system that incorporates nutritional management and preferential retrieval. In the preferential retrieval system, a recommender agent takes account of user tastes to extract and present menus. The user then, evaluates the menus recommended by various agents. Each recommender agents evolves on the basis of these menu appraisals. Over time, the preferences of the agents become similar to those of the users, resulting in menus that correspond to user tastes. This study thus utilizes an interactive immune algorithm (IIA) to optimize the preferential retrieval system. We tested the proposed system with a simulated user but genuine recipe data.

1 Introduction

It is difficult for cooks to device a new menus on a daily basis. Thus, cooks often consult Web sites when they need inspiration for their menus. However, contemporary recipe retrieval sites generally retrieve a recipe by using either a keyword or a popularity rank. Under these conditions, the taste preferences of a user are not considered, so the sites retrieve the same recipes for multiple users. Therefore, we propose a support system for healthy eating habits that considers the dietary needs and taste preferences of a user without prompting for keywords.

A preferential retrieval system was investigated in a previous study [1]. this conventional system learns user preferences through interactive genetic algorithm (IGA). However, when a user has a variety of preferences, the conventional system is hard put to learn the user's various preferences. In fact, the IGA of the conventional system converges to a single local solution. If the system continually makes recommendations that match one preference, the user may feel discontente. Thus, the system needs to recommend a variety of recipes that matches the breadth of a user's tastes.

In this paper, we propose a preferential retrieval system that employs an interactive immune algorithm (IIA). The proposed system can make recommendations

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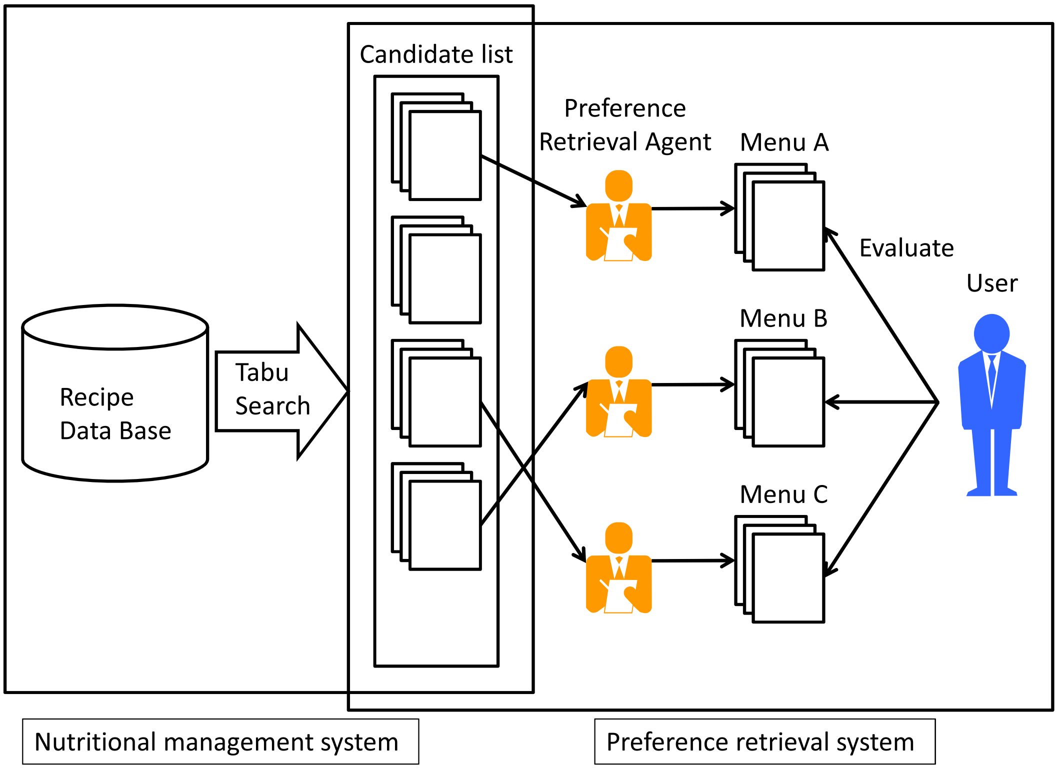

Fig. 1. Support system for healthy eating habits

to users in accordance with their preference. We focus on describing the preferential retrieval system and the simulations performed.

2 Support System for Healthy Eating Habits

2.1 System Framework

The support system for healthy eating habits is shown in Fig. 1. The support system consists of a nutritional management system and a preferential retrieval system. The nutritional management system was developed in a previous study [2]. Its database contains recipe data. The nutritional management system first uses the tabu search method to create nutritionally balanced menus that combine multiple recipes and then stores the generated menus in a candidate list. The preferential retrieval system recommends menus and learns user preferences. Its preferential retrieval agent uses the co-evaluation model and the only evaluation model proposed in a previous study [3]. Based on the stored information about user preferences, the agent searches the candidate list and selects a menu that the agent estimates will be approved by the user. The agent recommends the selected menu to the user. The user then evaluates the menus recommended menu by several agents. By repeating these operations, the agents can learn the various preferences of the user and recommend a greater diversity of appropriate menus to the user. In this manner, the agents evolve based on the evaluations by users.

2.2 IIA

In this study, the preferential retrieval system uses the IIA to learn the preferences of users [4]. The evolution starts with a population of randomly generated individuals. In a genetic algorithm (GA), each individual is represented by a so-called antibody. With every new generation, the fitness of each antibody is evaluated by the user, and the concentration of each antibody is calculated from the degrees of similarity between the pairs of antibodies. The degree of similarity is a measure of the extent to which the genetic information of one antibody is similar to that of the other antibody. A pair of antibodies with a degree of similarity that exceeds a threshold are called - similar antibodies. The concentration of a given antibody refers to how many similar antibodies exist among the other antibodies. The antibodies that exceed a concentration threshold are separated into memory cells and suppressor cells. Antibodies similar to the suppressor cells are erased. The expected value of each antibody is determined by its fitness and concentration. Multiple antibodies are stochastically selected from the current population on the basis of these expected values. In addition, the selected antibodies are modified by crossovers and mutations to form a new population, which is used in the next generation. The algorithm is terminated when the maximum number of generations has been reached. The well-known interactive evolutionary computation (IEC) generates solutions (antibodies) that are presented to the user. In other words, systems using IEC cannot learn preferences of users. Furthermore, systems using IEC require users to evaluate the evolving solutions repeatedly. Thus, increasing the burden that a user bears for evaluating will negatively affect the optimization performance. The preferential retrieval system can solve these issues using a preferential retrieval agent by the co-evaluation model and only evaluation model.

2.3 Preferential Retrieval Agent

The preferential retrieval agent implements a model to decode information about the user's preferences and retrieve a menu from a candidate list. That is, the agent can recommend menus for users according to their preferences. In this preferential retrieval system, the agent is optimized by including the IIA, which enable the agent to learn information about user preferences.

2.4 Co-evaluation Model

A preferential retrieval agent evolves by learning from a user's evaluation of a recipe that was presented to the user. However, an agent designed using the co-evaluation model also consider the evaluations of recipes presented by other agents. The agent evaluates all recipes that are presented to the user based on the information about the user's preferences. Conversely, the user evaluates all recipes that are presented by agents. The closer the evaluation by the user and the evaluation by the agent, the greater is the amount of consideration given by the agent. Using the co-evaluation model, the agent can obtain more information for its self optimization. Moreover, applying the co-evaluation model reduces the number of times that a users needs to evaluate data.

2.5 Only Evaluation Model

The optimization performance of the IIA can be improved by increasing the number of antibodies (agents). However, this increases the user's burden of evaluating recipes, because the number of recipes is the same as the number of agents. Therefore, this study uses an agent that employs the only evaluation model. Even though this agent is optimized using the co-evaluation model, it does not present menus to the user. Thus, by using the only evaluation model, the optimization performance of the IIA is enhanced without increasing the user's burden.

3 Simulations

3.1 Overview

In this section, we discuss the simulations that were performed to measure the optimization performance of the agent. The records of past evaluations by a user were exploited to improve the performance in the simulations. Thus, we replaced a real user with a simulated user. The simulated user was provided with some preferences to represent the variety of the real user's preferences. Hence, the simulated user evaluated the presented data using the same criteria as the real user. The most favorable evaluation was taken as the evaluation of the data presented. The number of generations of evaluation records was 20 when using the preferential retrieval system. We used 180 elements of the cooking ingredients as the recipe data. The output of each simulation was the error between the evaluations by the best preferential retrieval agent and the simulated user.

3.2 Results

The errors output by the simulation are shown in Table. 1, where GA denotes genetic algorithm, IA denotes the immune Algorithm, and NO denotes a nonoptimized agent. Table. 1 shows that the IA is preferable to the GA and the NO.

The simulation output related to learning a variety of user preferences is shown in Table. 2, which confirms that the GA can learn only a single user preference but the IA can learn a variety of user preferences.

3.3 Discussion

This study demonstrates how an agent in a preferential retrieval system can learn the preferences of a user. Such agents can thus recommend menus according to the preferences of users. In addition, this study demonstrates that the IIA can learn more of a user's preferences than the IGA. One limitation of this study is that all of the experiments were conducted with one simulated user instead of real users.

Table 1. Comparison of average errors of the IA, GA, and NO

Method - variety of poreferences	GA - 1	GA - 3	GA - 5	IA - 1	IA - 3	IA - 5	NO - 1	NO - 3	NO - 5
Average error	1.49	1.69	2.00	0.61	0.60	0.67	2.37	2.40	2.52

Table 2. Comparison of average learning

Method - variety of poreference	GA - 1	GA - 3	GA - 5	IA - 1	IA - 3	IA - 5
Average Learning variety of preferences	1	1	1	1	2.2	3.4

4 Conclusions

In this paper, we proposed a support system for healthy eating habits. We described not only the support system itself but also the simulations performed using this system. The preferential retrieval system learned the user's preferences using the preferential retrieval agent. Moreover, the preferential retrieval system exploited this information about the user's preferences to recommended menus that pleased the user. Through simulations, we confirmed the effectiveness of the optimization performance of the agent. In particular, we demonstrated that the IIA can learn more of a user's preferences than the IGA. As part of future work, we plan to test the effectiveness of this method further by applying it for real users instead of a lone simulated user in future.

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