A Method of Using Experts' Life Logs to Enhance Users' Motivation

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Abstract

In this paper, we propose a method of enhancing a user's motivation to improve his/her level of skill in a given field. Currently, because of the reduced size of various sensors and the smaller number of handheld devices on board them, it is becoming easier to collect life logs in the real world such as those for GPS, acceleration data, and pictures. On the other hand, because of the appearance of blogs, social network services (SNSes), and Twitter, it is becoming easier to collect life logs in cyberspace. Under these circumstances, "expert" users are appearing who record know-how in and release it from a life log in an attempt to achieve certain aims. Also appearing are users who are affected by experts and who also make efforts to achieve aims by recording know-how in a life log. We here report our attempt to achieve a method of enhancing users' motivation to start making self-active efforts in this regard. The method is to automatically select experts who can inspire users and be a good reference for them, then to present the experts' life logs to the users. To achieve this, we propose a quantitative evaluation index between the life logs of experts and users from the viewpoints of similarity and difference. The greater the difference between the user's current level of skills and the expert's level of skills is, and the greater the similarity between the user's current feature quantity and the expert's past feature quantity is, the higher the proposed index becomes. Experiments in presenting experts' life logs to users to enhance the users' motivation verified the possibility that the higher the proposed index of experts is, the higher is the rate achieved of motivating users to start self-active efforts.

1. Introduction

Currently, it is becoming easier to collect life logs in the real world and in cyberspace with the advent of sensors, GPS devices, Twitter, and SNSes. Under these circumstances, many experts' records regarding know-how and efforts have been released as books and blogs. This increases the chance to utilize such records as life logs. We define "experts" as those who are at a higher level of skill than general users in a certain field. We define "life logs" as information about users' past, including information that users recorded by themselves. Moreover, ordinary users who are affected by experts and make an effort to achieve an aim by recording life logs are now appearing.

The purpose of our research is to establish a systematic method of enhancing a user's motivation to improve his/her level of skill by utilizing life logs of both experts and users. We therefore based the stages we set for enhancing user's motivation on those given in [1]. The stages are as follows.

- Precontemplation: User isn't interested in the field.
- Contemplation: User is interested in the field, but doesn't make efforts.
- Action: User makes efforts in the field.
- Maintenance: User makes efforts over a certain period.

In our work, we focused on getting users to advance from the "contemplation" stage to the "action" stage, encouraging them to start making efforts.

The rest of the paper is organized as follows. Section 2 describes previous work done in this area and Section 3 proposes our method of presenting experts' logs to users. In Section 4, we describe an experiment we conducted to evaluate the method's validity. Section 5 concludes the paper with a brief summary of key points.

2. Previous work

There is published work in which a user's life log is matched with another user's life log and the life logs are utilized in facilitating user efforts. Y. Wada et al. conducted research on a recommendation method regarding e-learning [2]. Their system estimates the number of times a user has accessed educational material by using the number of access instances of another user who has a similar access log. The system then recommends educational materials it estimates the user will access a large number of times.
There is also published work in which a user's efforts are facilitated by utilizing experts' life logs. S. Saga et al. conducted research on a way to present experts' life logs in calligraphy to users [3]. Their system, in which experts' records of calligraphy brush strokes and pressure are provided to users, aims to facilitate the users' efforts and help them improve their level of skill.
However, we need a more efficient and systematic method to achieve the aim of our work. As described above, the system reported in [2] recommends educational materials to users by matching the life logs of users who show similarities in terms of actions they have taken. This method cannot, however, determine whether the first user is an expert who has succeeded in improving his/her level of skill. Therefore, the recommended content may not be particularly interesting for the second user and if not it is doubtful that even following it would help improve the user's level of skill. In the system reported in [3], the life log of an expert who has succeeded in improving his/her level of skill in calligraphy is reported to a user. The life log's content may appeal to users who are interested in calligraphy. However, it is difficult to say that this system alone will help users to start making efforts to improve, because it does not present anything to the users that will help them raise their skill level; they have to obtain greater skills through their own efforts.

3. Matching experts for users

3.1 Method and System's process flow

The system we describe here makes use of points of appeal in the expert's life log and the similarity between the user's life log and that of the expert. Moreover, the system brings about the effect of making users think that they can improve their skill level. By making use of the effects of "Points of appeal" and "Possible skill level improvement", the system is able to help users start to make efforts (Fig. 1).
Fig. 2 shows the system's process flow. The user's life log and that of multiple experts are collected on the terminals of the user and each of the experts and stored in the DB (database) on the matching server. The format of life logs is [date, level of skill, attribute, life pattern]. After the matching process module receives the experts' life log and the user's life log from the DB, it matches the user with experts who can inspire and be a good reference for him/her. The user's terminal receives the life log of experts matched by the module and presents it to the user. Of these process steps, we concentrate on the one that matches the user with experts.

3.2 Degree of Gap Matching

We here describe DGM (Degree of Gap Matching), a quantitative evaluation index we propose that is criterial for matching an appropriate expert to a user based on a life log. We propose the index based on two perspectives: "Points of appeal" and "Possible skill level improvement". We formulate the index as follows:

$$DGM = \sum_{k=1}^{m} w_L[k](L_{Ec}[k] - L_{Fc}[k]) + \sum_{k=1}^{n} \frac{w_X[k]}{|X_{Ep}[k] - X_{Fc}[k]| + 1} + \sum_{k=1}^{m} w_T[k] \frac{(L_{Ec}[k] - L_{Ep}[k])}{t} \quad (1)$$

$L[m]$ is the vector of skill level (m is the number of skills), and $X[n]$ is a feature quantity (n is the number of features). t means the expert's total effort time from past to present. With regard to the suffixes of L, X, E means "expert", F means "user", c means "current", and p means "past". w is the weight of each element in its respective term. Feature quantity is a life log whose format is [date, level of skill, attribute, life pattern].

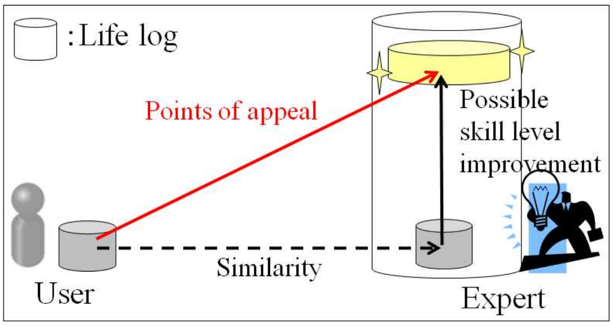

Fig. 1. Support in starting efforts

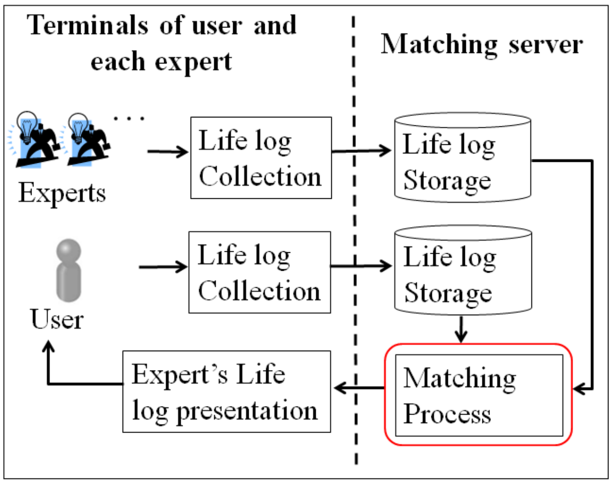

Fig. 2. System process flow

The greater the difference between the user's current level of skills and the expert's level of skills is, the higher the first term in expression (1) becomes. The more similar a user's current feature quantity and an expert's past feature quantity are, the higher the second term in expression (1) becomes. The more the expert improves his/her level of skills in the shorter amount of time, the higher the third term in expression (1) becomes. As described above, the system matches a user to an appropriate expert who encourages the user to start making efforts.

4. Evaluation

To evaluate the validity of the proposed method of matching appropriate experts to users, we presented experts' life logs to users and had the users answer a questionnaire about motivation.

4.1 Experimental objectives

The experimental objectives were:

- To analyze the effective terms in DGM.
- To verify that the higher DGM an expert has, the more the user's motivation is enhanced.

4.2 Experimental environment

We conducted an online questionnaire with the support of an Internet research firm. The experiment participants (hereafter "examinees") comprised 155 men and women aged 20-60. For the fields in which efforts are made, we selected foreign language (English) and bookkeeping as "mental" fields and golf and dieting as "physical" fields. We selected these fields because many people are interested in them and because it is easy to quantify skill level in them. Each examinee answered one questionnaire in one field. The number of examinees in each field is as follows:

- Foreign language (English):46
- Bookkeeping:37
- Golf:42
- Dieting:30

The criteria for measuring level of skill in each field are as follows:

- Foreign language:TOEIC score (10-990)
- Bookkeeping: Bookkeeping exam level (levels 1-3)
- Golf: Golf score
- Diet: Amount of weight loss

We stipulated that all examinees had to be people in the "contemplation" stage (Fig. 1). They also had to have skill level less than a given threshold value (e.g., 600 TOEIC points) and fall under the "make little or no efforts in the field" category (less than one hour per week).

4.3 Experimental procedure

The experimental procedure was as follows.

- We had the examinees fill in the feature quantity input form, the items of which include level of skill, attribute, and life pattern.
- We created a virtual life log of 30 experts based on the examinees' feature quantity forms and presented that virtual life log to one examinee.
- We asked each examinee the question, "Did the information you were given about the expert enhance your motivation to make efforts?" for each of the 30 experts. The answers are on a five-point scale: 1.Not at all / 2.Only slightly / 3.To some degree / 4.Very much so / 5.Extremely so

4.4 Evaluation method

We conducted two main evaluations. In the first, we analyzed effective terms in DGM by multiple regression analysis and AIC. We conducted a hypothesis test toward a null hypothesis; that term's weight is zero. Thus, we regard terms for which p-value < 0.1 holds as effective terms.
In the second evaluation, we analyzed the relationship between DGM set up by LOOCV (Leave One Out Cross Validation) and actual questionnaire scores. LOOCV is an analysis method that sets one out of n data as test data, sets the other data as training data, then repeats learning n times.

4.5 Experimental results and discussion

Table 1 shows the effective term analysis results. It can be seen that "age similarity" is effective in all fields. "Difference in level of skill", "similarity in level of skill", and "efficiency" are effective in three of the four fields.

Fig. 3 shows the relationship between a DGM set up by LOOCV and an actual questionnaire score as a box-and-whisker plot. We conducted LOOCV by using data about all of the examinees in each field. The horizontal axis is an expert's DGM that is set up by LOOCV which sets the expert as test data, and the vertical axis is the questionnaire score that each user gives each expert. From the results shown in Fig. 3, we verified that a moderately positive correlation (> 0.4) existed in all fields except for dieting. Additionally, over 90% of the scores of experts whose DGM was over 3.1 were 3 ("Enhanced to some degree") or higher in the foreign language and golf fields. In the bookkeeping field, over 90% of the scores of experts whose DGM was over 3.3 were 3 or higher. This verifies the possibility that the higher the DGM of experts is, the higher the rate of motivating users is.

5. Conclusion

In this paper, we proposed a method of having users start making self-active efforts to improve their levels of skill in a field by enhancing their motivation to do so. The method is one of automatically selecting experts who can inspire users and be a good reference to them and providing their life logs to users. To achieve this, we propose DGM, which is a quantitative evaluation index between the life logs of experts and users from the viewpoints of similarity and difference. Experimental results in presenting experts' life logs to users verified the possibility that the higher the DGM of experts is, the higher is the rate of motivating users to start making self-active efforts.

References

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Table 1. Effective term analysis results

		Foreign language	Book-keeping	Golf	Diet
Difference of level of skill		○	○	○	
Similarity	level of skill	○	○	○	
	age	○	○	○	○
	gender			○	○
	origin				
	address				○
	family size				
	the number of holidays				○
	overtime hours	○		○	
	commute time		○		
	time spent to TV/radio				
	time spent to pastime				
	time spent to sport			○	○
Efficiency		○	○	○	
Difficulty	age				
	overtime hours				
	daily life patterns in terms of time spent				

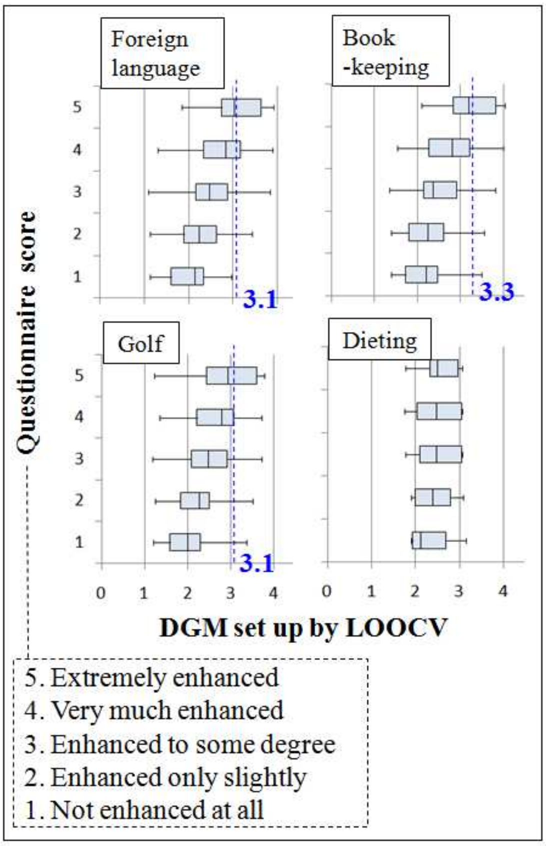

Fig. 3. Relationship between DGM and actual questionnaire score toward each expert