Personalized Robotic Service using N-gram Affective Event model

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***Abstract*—N-gram affective Event model which consists of 5W1H event episode ontologies and affection ontologies is suggested for personalized robotic service. Nowadays, personalization technology is increasingly becoming an essential component in education. Here, robotic service can be another field to meet personal need. The case study shows that even though two students missed same question, robots suggests different reviews according to the his own personal tendency.**

I. INTRODUCTION

Service tasks frame the situation where service tasks are carried out in an individual way and service flow patterns as their own sequence forming a very flexible sort of subsequence [1]. Recently, there are strong tendency to regard educational service robots as "the companion of humans", which can provide educational robot contents and educational services. However, the current service robots can be more holistic systems to offer personalized robotic services to satisfy every individual by accommodating the differences between individuals reflecting their preferences. Hybrid approaches of personalization technology that combine collaborative filtering approaches and content-based approaches are proposed over the last decade. Especially, n-gram based approaches are proposed to utilize path profiles from very large data sets to predict the users' future requests.

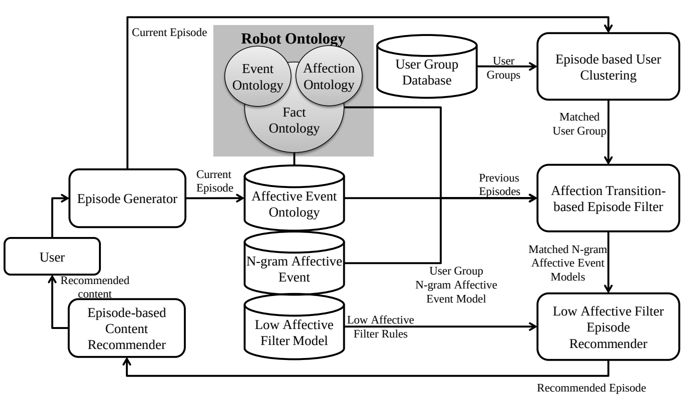

Fig. 1. Overall architecture of proposed approach.

II. OVERALL ARCHITECTURE

Figure. 1 shows the overall architecture for personalized robotic service. When there is an episode composed with 5W1H ontology which describes a current situation more correctly, user's group is matched by episode based clustering method. Similar n-gram affective events are selected by compared with current episode and previous episodes in matched user group. Among them, an last episode of n-gram is recommended by low affective filter rules which allow more input for learning. Then, a robot offers a service corresponding with the current episode from the episode.

III. N-GRAM AFFECTIVE EVENT MODEL

We exploited the hybrid filtering method that discovers the neighborhood of the active user having similar n-gram affective events where n-grams are frequent sequential patterns of n items which enable to predict the user's the next pattern. In this paper, the affective event ontology is used as an element of pattern as shown in Fig. 2.

A. Affection-based Episode Ontology

Episode ontology [2] is used to describe the temporal information according to the start and end time of each past episode, as shown in the upper part of Fig. 2. For example,consider that a robot recognized the following context; "From 2011-09-09 14:00:00 to 15:00:00, Student_1 trained words at the cyber-class for exercising. He is bored". Then, the affection-based episode ontology consists of when (2011-09-09 14:00:00 - 15:00:00), where (LectureRoom), who (Student_1), why (Exercise), what (Word), how(Training), and affection (Bored). Additionally, all the elements of affection-based episode ontology are instances of the fact ontology for robot knowledge representation [3]. To calculate the similarity between affective events, the taxonomy similarity proposed by Resnik [4] is used, as

$$fs_t(x_i,\ x_j)\ =\ 1\ -\ \frac{d_t(x_i,\ x_j)}{\max_{(z_1,\ z_2)\ \in\ D_t\times\ D_t}\ d_t(z_1, z_2)},$$

$fs_t()$ is similarity function between two instances where

$$d_t(x_1, x_2)\ =\ -\log\left(\frac{p_1 p_2}{P^2_{LCA(x_1,x_2)}}\right),$$

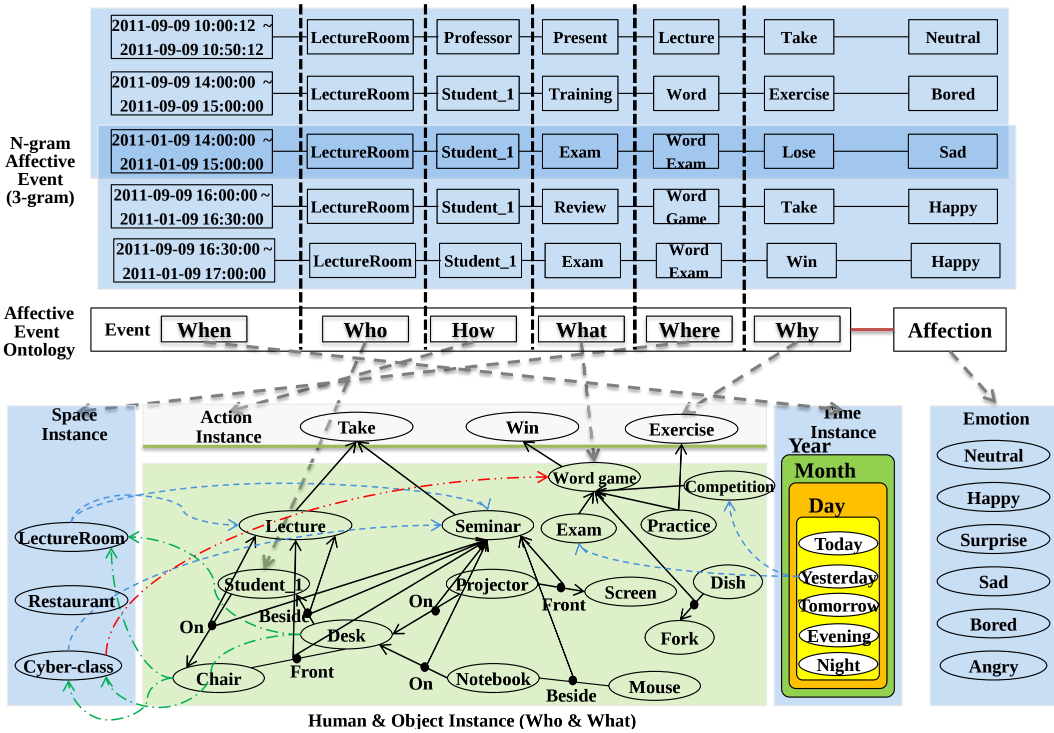

Fig. 2. N-gram affective event, affection-based episode ontology and fact ontologies.

$LCA(x_1, x_2)$ is the lowest common ancestor of x_1 and x_2 and $\max_{(z_1,\, z_2)\, \in\, D_t \times\, D_t} d_t(z_1, z_2)$ means the longest distance among the ontology concept. Using taxonomy similarity, event similarity is calculated as summation of each element of the affective event. If the emotions of episodes are different, the similarity is zero, as

$$s_e\left(ae_1\ ,\ ae_2\right) = \left\{ \begin{array}{ll} \sum_{i=2}^{6} fs_t\left(w_{i1}\ ,\ w_{i2}\right) & ,\ if\ em_1 = em_2 \\ 0 & ,\ if\ em_1 \neq em_2 \end{array} \right\}.$$

B. N-gram Affective Event

Especially, n-gram based approaches where n-grams are frequent sequential patterns of n items are proposed to utilize path profiles from very large data sets to predict the users' future requests [5]. The similarity between n-gram affective events is calculated as summation of each element of n-gram, as

$$s_g = \frac{1}{n} \sum_{i=1}^{n} s_e\left(G_{1i}\ ,\ G_{2i}\right),$$

where G_1 and G_2 are n-gram and n is the number of n-gram as events consisting of event sequences. Finally, user similarity is calculated as,

$$s_u\left(AE_1\ ,\ AE_2\right) = \tfrac{1}{n+m} \left\{ \sum_i \max_j\ s_e\left(AE_{1i}\ ,\ AE_{2j}\right) + \sum_j \max_i\ s_e\left(AE_{2j}\ ,\ AE_{1i}\right) \right\}$$

IV. Case Study

To evaluate the proposed approach for personalized robotic service recommendation , we applied the scenario of English learning. Even though two students missed same question about 'tiger', robots suggests different reviews according to the his own personal tendency. Audio contents are suggested for one. On the other hand, images are suggested for the other. Finally, both can solve the word quiz.

V. Conclusion

This paper proposed hybrid filtering method with n-gram affective event ontology. It enables a service robot to offer personalized robotic service.

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