A Case-based Reasoning Approach for Automated Facilitation in Online Discussion Systems

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***Abstract*—Online discussion systems have recently attracted great attention as an enabling approach of realizing collective intelligence. During online discussions, human facilitators are introduced in order to help these discussions to proceed more efficiently and productively. However, there are a number of challenges such as human bias and time restriction that need to be solved in the human facilitator-based online discussion systems. As a result, automated facilitation becomes necessary in order to overcome these shortcomings. This paper proposes a novel approach for automated facilitation that utilizes case based reasoning (CBR) in order to imitate the human facilitator thinking style. The proposed approach works in issue based information system (IBIS) discussion style where complex problems are designed as a conversation amongst several stockholders. These stockholders, in turn, bring their expertise in order to resolve the discussion point. Experimental results show the ability of the proposed approach to improve the performance of online discussion systems, and to guide the online discussion towards consensus and towards gathering wisdom efficiently.**

***Index Terms*—collective intelligence, online discussion system, automated facilitation, issue based information systems, case-based reasoning**

I. Introduction

With the development of information technology, people from all over the world can communicate with each other via Internet in different ways such as email, blog and social networks. As more and more people join in the Internet, it becomes possible for people to cooperate with each other to solve problems which are difficult for individuals and small groups. One of the famous examples of these problems is DARPA Network Challenge which asks participant teams to search for ten red balloons that are located all over the United States [1]. And the result is that the successful team, i.e., MIT team, has completed the challenge in less than nine hours. This sort of intelligence is called collective intelligence which is shared or group intelligence that emerges from the collaboration, collective efforts, and competition of many individuals and leads to consensus decision making [2]. With the help of collective intelligence, a large number of people can cooperate together to solve large-scale problems.

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One of the famous examples of utilizing collective intelligence is online discussion systems. These systems utilize human facilitators to conduct facilitation in order to guide the online discussion towards consensus. However, human facilitators based online discussion systems face several challenging problems such as human bias, time restriction and human resources constrains. As a result, it is necessary to develop automated facilitation approaches in order to support these online discussion systems. Towards this end, this paper proposes a novel approach for automated facilitation based on CBR. The proposed approach utilizes CBR reasoning paradigm in order to imitate the human facilitator thinking style.

The rest of this paper is organized as follows. In section II, we introduce an overview of online discussion systems and the challenges they currently face. Also, we introduce the reasons for choosing CBR as a potential solution to address these challenges. In section III, we describe the proposed CBR-based approach for automated facilitation. Section IV presents the implementation of a prototype automated facilitation agent. Section V discusses the future of this research. Section VI introduces the related work of this research.

II. Motivation

A. Online Discussion Systems

Online discussion systems have attracted a great deal of research interest in recent years [3] [4]. These systems represent a promising and emerging approach to promote the decision situation when large numbers of roles are involved in decision making process. One famous example is Climate CoLab [3], which utilizes online discussions in order to receive arguments that aim to solve global climate problems. Towards this end, it develops an online platform which is used to facilitate large-scale discussions amongst several participants. Another successful example is Collagree [4], which is an online discussion support system that has been used in order to gather Nagoya City Planning opinions from Nagoya citizens. In this regard, Collagree helps to build consensus effectively by using mechanisms such as facilitation, discussion-tree and incentives. Both systems make it possible for people to easily participate in discussions with less physical limitations.

However, these online discussion systems face several challenges. For example, they face challenges in guiding participants in a productive manner to choose the best opinions from what they have gathered [5]. Also, these online discussion systems still face several problems that need to be solved such as solution generation [6], solution evaluation [7], idea filtering [8], and process management [5]. As a result, it is critically needed to develop useful techniques in order to guide the online discussions towards consensus, and to gather wisdom efficiently.

One successful approach to improve the performance of the online discussion systems is to use the help of human facilitators [9]. Towards this end, human facilitators promote the development of the discussion, integrate ideas and opinions, and help the group to build consensus. However, there is a human bias that cannot be avoided during the facilitation process when we use the help from human facilitators. In addition, with the time restrictions of human facilitators, it becomes difficult to let the discussion be in progress continuously. Moreover, when considering large-scale discussions, large numbers of participants and opinions need to be handled. Therefore, it becomes impossible for human facilitators to handle such large-scale environments where posts increase exponentially and the number of participants is open and may change over time. As a result, there exists an urgent need to develop more advanced techniques that are able to support the automated facilitation in order to guide the participants towards consensuses efficiently.

In order to facilitate online discussions automatically, some key challenges need to be considered. Firstly, it is necessary to encourage participants to generate high quality ideas without redundancy. Also, when generating ideas, it is recommended to consider other submitted ideas before generating a new one. Secondly, with the development of the discussion, consensus points should be decided where the content is mature and ready to be agreed upon. At the same time, attention should be paid to the topics where discussions have not developed yet. Thirdly, facilitation should be conducted when unproductive behaviors such as groupthink, which means prematurely settling on a solution without sufficiently exploring the space of other promising alternatives [10], and divided opinions take place.

Towards this end, several research efforts have been proposed in order to promote automated facilitation from different perspectives [11] [12]. However, to the best of our knowledge, there is no research that attempts to create automated facilitation mechanisms by imitating the human facilitator thinking style. When human facilitators attempt to solve the above-mentioned problems, they try to find similar solutions from their past experiences. Because in different topics and different situations, it is impossible for human facilitators to understand all the posted information thoroughly, especially when the posted information contains highly professional knowledge. In this context, human facilitators are able to recognize the situation of which stage the discussion is, by utilizing their past experience on a similar situation. Therefore, if we consider developing automated facilitation agents, it becomes a critical challenge to generate and utilize these sorts of human experience. In addition, because of the existence of various parameters in different discussion topics, it also becomes difficult to use metrics to define a unique discussion situation. In addition, it is not possible to define general rules of how to conduct constructive facilitation. As a result, there exists a need to consider a novel approach to solve these problems from the point of utilizing the past discussion cases, like human facilitators, rather than specific rules.

B. *Case-based Reasoning*

In order to develop automated facilitation agents, several techniques such as computer reasoning and cognition are promising to be applied. One of these techniques is case-based reasoning(CBR) [13]. CBR provides an effective reasoning paradigm for solving new problems by adopting similar solutions that have been proposed for similar problems in the past. A general CBR-based system can be described by a four steps reasoning cycle as follows [14].

- Retrieve the most similar case from a case base
- Reuse the solution of the most similar case to solve the current problem
- Revise the proposed solution if necessary
- Retain the parts of this case into a case base for future problem solving

When considering using CBR as the solution to solve a problem, it is not necessary to understand the specific rules inside the problem itself. It is rather important to find the essential characteristics which are used to express this problem. Once the problem has been defined and solved successfully, it is regarded as a case which will be used as a reference in the future. When attempting to solve a new problem, the system looks for the most similar case that happened before and recommends solutions that were used in that case.

As a result, in our research, CBR is proposed as a suitable solution for the automated facilitation domain. Using CBR, the system defines different discussion scenarios as different cases without considering specific discussion contents. Generated cases are stored in the system as past experiences, which are then used as references to decide whether facilitation is needed or not. By using CBR, these experiences are reused by the system in order to conduct automated facilitation the same way that human facilitators are doing facilitation. In addition, CBR has been widely applied in real-world applications such as fault diagnostics [15] and judge support system [16]. Based on these successful applications that have been developed, we propose CBR cognition paradigm as a promising approach in order to develop automated facilitation agents in online discussion systems.

III. CBR BASED AUTOMATED FACILITATION APPROACH

In this research, we propose a CBR based automated facilitation approach in IBIS style discussion systems. IBIS style is based on the principle that the design process for complex problems is fundamentally a conversation amongst several stakeholders [17]. These stakeholders bring their respective expertise and view points to the resolution of these design issues. In IBIS-style discussion systems, discussion components appear in a systematic structure. One of the notable IBIS based discussion systems is Deliberatorium [18], which is a large-scale discussion system that provides a simple systematic structure. In Deliberatorium, issue, idea and argument appear in a systematic structure. Therefore, this system is able to radically reduce redundancy and encourage clarity.

In order to enable a discussion to proceed efficiently and constructively, automated facilitation agent needs to decide whether the discussion is in a state that needs to conduct facilitation and the sort of facilitation that is necessary. Towards this end, the proposed CBR-based automated facilitation approach works as follows.

A. Case Generation

For every IBIS style discussion system, we generate an IBIS structure to show how the discussion proceeds. In IBIS structure, posted discussion information is represented by different sorts of elements such as issues, ideas and arguments. In different discussion scenarios, the IBIS structures of these scenarios are different. As a result, we can extract the characteristics of the situations specifically whether facilitation should be added. For example, the IBIS structures of a certain discussion can be generated as demonstrated in Fig. 1. In Fig. 1, issues mean the discussion case generated by participants that needs to be solved. Idea means the proposition that participants generated to solve the relevant issue. Argu means the arguments that participants have about this idea.

As shown in Fig. 1, in Case A, it is clear that Issue1_2 is better discussed than Issue1_3 because more ideas are generated during discussing this issue. Therefore, there is a basic need to add facilitation support in order to encourage participants to generate more ideas about Issue1_3 in this situation. Similarly, in Case B, it is clear that both Issue2_2 and Issue2_3 need to be facilitated to get more ideas. As a result, we believe that whether facilitation should be added can be decided from the perspective of the discussion structure.

B. Case Definition

After generating the IBIS structure from the online discussion topics, we have a clear understanding of the discussion topic itself in terms of issues, ideas and arguments. Then, each discussion topic is represented by a separate discussion case. In this regard, each discussion case, in turn, is represented by a number of quantitative parameters. One example case is shown in Table I.

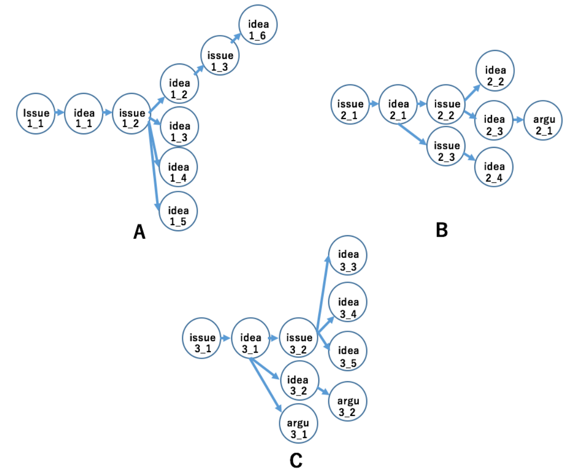

Fig. 1. IBIS Structure of Three Discussion Cases

TABLE I
CASE DEFINITION

	Attribute	Type	Meaning
D	ID	int	Identification of a case
	Duration	int	Duration of the discussion time
	Idea Number	int	Number of the generated ideas
	Argument Number	int	Number of the generated opinions
	Idea Speed	int	Speed of generating ideas
	Argument Speed	int	Speed of generating arguments
	Idea Depth	int	Idea depth of the issue
S	Facilitation	bool	Whether facilitation has been added

As shown in Table I, the attributes in Category D are designated for case description which reflects the situation of the discussion. In specific, ID is used to identify the case. Duration means the duration of the discussion time. Idea number means the number of the generated ideas. Basically, more ideas mean more information has been generated in order to resolve this issue. Argument number means the number of generated opinions related to the relevant idea. Basically, more arguments mean participants have more definite opinions to the relevant idea. Idea speed means the speed of generating ideas. Idea speed can be calculated by using idea number divided by duration. In this regard, higher idea speed means the topic is deeply discussed in the relevant discussion time than another discussion topic with a lower idea speed. Argument speed means the speed of generating arguments. Argument speed can be calculated by using argument number divided by duration. In this regard, higher argument speed means the topic is deeply discussed in the relevant discussion time than another discussion topic with a lower argument speed. Idea depth means the highest idea depth of the issue. For instance, as shown in Fig. 1, Issue1_1 has an idea depth which is 3 while Issue3_1 has an idea depth which is 2. Higher idea depth means the relevant issue is better discussed than another issue with a lower idea depth.

The above attributes in Category D are set to let the automated facilitation agent decide the state of the current discussion and whether facilitation is necessary or not. In turn, the decision of whether there is a facilitation needed in this sort of situation is recorded in Category S.

C. Case Adaptation

After we retrieve the most similar case from the case base, we receive the result that whether facilitation is needed. If facilitation is needed in this situation, we also receive the feedback of what sort of facilitation needs to be applied. This sort of facilitation is applied to the new discussion case. After applying the received facilitation to the new discussion case, it can be determined that whether it is efficient or not. If the received facilitation does not match well, it should be adapted to be suitable and added to the case base as a new case.

IV. Prototype Implementation

In this section, we introduce the prototype of the automated facilitation agent based on the proposed CBR approach. In specific, we introduce the calculation method that is used to find the most similar case from the case base. After that, we introduce a working example to demonstrate the efficiency of the proposed CBR-based approach in the automated facilitation of online discussion systems.

A. Similarity Calculation

Based on the case definition and attributes that are introduced in Table I, it is necessary to provide an algorithm in order to calculate the similarity between two cases. The similarity calculation algorithm is important in order to retrieve the most similar case from a case base. In this research, we use (1) to calculate the similarity between two cases as follows.

$$sim = \frac{\sum_{i=1}^{N} \omega_i sim_i(f_i, f_i')}{\sum_{i=1}^{N} \omega_i} \tag{1}$$

Where sim is the global similarity of two cases. N is the number of features or attributes that contribute to similarity. ω_i is the weight coefficient of each feature. sim_i is the local similarity of feature i. f_i and f_i' are the i^{th} features in one case. We use Nearest Neighbor(NN) algorithm [19] to calculate the similarity of these features.

B. Case Retrieval

In order to demonstrate the ability of the proposed CBR-based approach to retrieve similar discussion cases efficiently, we built a synthetic test case base that includes five discussion cases. This case base is shown in Table II.

Based on the information in this case base, we can retrieve the most similar case from the case base using the similarity calculation algorithm that was introduced in the previous subsection. Please note that when calculating similarity, each attribute is given the same weight.

A demonstrating example of the case retrieval works as follows. When we receive a new discussion case which is represented in Table III as Case 6. We use the similarity calculation algorithm in order to retrieve the most similar case from the case base, i.e., Case 4. As a result, it is concluded that it is necessary to add facilitation support to Case 6. On the other hand, for Case 7 in Table III, the similarity calculation algorithm is used in order to retrieve the most similar case from our case base, i.e., Case 3. However, it is concluded that it is not necessary to add facilitation to Case 7.

TABLE II
Synthetic Cases in Test Case Base

ID	1	2	3	4	5
Duration(s)	120	120	60	100	100
Idea Number	1	3	3	1	5
Argument Number	2	4	3	1	5
Idea Speed	0.008	0.025	0.05	0.01	0.05
Argument Speed	0.017	0.333	0.05	0.01	0.05
Idea Depth	1	1	2	1	3
Facilitation	1	0	0	1	0

TABLE III
Synthetic New Test Case

ID	6	7
Duration(s)	90	120
Idea Number	1	6
Argument Number	1	6
Idea Speed	0.009	0.05
Argument Speed	0.009	0.05
Idea Depth	1	2

C. Case Reuse and Retain

After retrieving the most similar case from the case base, the recommended facilitation scenario that is included in this case can be reused. By reusing the recommended facilitation scenario, we provide the most suitable sort of facilitation support for the current discussion situation. In this context, Natural Language Process(NLP) algorithms can be utilized. After reusing the recommended facilitation scenario, the intelligent facilitation agent conducts a review of this automatically generated facilitation scenario. If the automatically generated facilitation scenario does not match well, new facilitation scenario needs to be generated and added to the case base as a new case.

V. Discussion

This paper presents a CBR-based approach for automated facilitation in online discussion systems. One of the main tasks of the proposed approach is to check when it is necessary to add facilitation support to the online discussion. With properly added facilitation support, online discussions can proceed positively and towards consensus. This paper reports the research motivation and preliminary progress in this project. Other research work is still underway in order to address the following challenges.

A. Graph Similarity Calculation

When generating the discussion cases from IBIS structure, one challenging issue is how to measure the similarity among these discussion cases. At the moment, we represent each discussion case structure as a labelled graph. In this situation, both discussion label and discussion structure need to be considered. In addition, the integration of these two factors is also a challenging issue that needs to be solved.

B. Validation and Evaluation

Validation and evaluation is a challenging issue in developing efficient CBR-based systems. Therefore, it requires efforts to design the validation procedures and the evaluation metrics for the proposed CBR-based approach. As a result, in this research, the following tasks are planned for future work.

- Defining the different sorts of facilitation support that are needed.
- Collecting more data from online discussion systems and generating large case-bases.
- Evaluating the performance of the proposed agent for automated facilitation support by comparing its results with human facilitators.

VI. Related Work

In order to guide the online discussion towards consensus and towards gathering wisdom efficiently, several research approaches have been proposed from different perspectives. Ito et al. [4] introduced human facilitators to the online discussion systems in order to provide facilitation support during these online discussions. Another notable approach was proposed by Ito et al. [20] that uses incentive mechanisms in order to engage several participants in stimulating and active online discussions. Sengoku et al. [21] developed a tree diagram in order to help to visualize the flow of a discussion on the basis of the relationships amongst different replies in its online conversations.

From the perspective of structured discussion systems, Klein et al. [18] developed an IBIS-based online discussion system that is named Deliberatorium. In this system, tree-structured networks of posts were developed in order to improve the signal-to-noise ratio and to enable participants to receive a more complete picture of how to solve complex problems with far less efforts.

In the automated facilitation research domain, Wong et al. [11] designed effective facilitation modes for electronic meetings. In their work, these authors demonstrated that group meetings that are facilitated by automated facilitated mode generated more ideas than group meetings that are facilitated by novice-human facilitators. In this context, Adla et al. [12] developed a toolkit in order to help human facilitators to monitor and control the group decision making process.

VII. Conclusion

This paper proposed a novel approach to promote automated facilitation in online discussion systems by using the CBR cognition paradigm. The proposed approach adopts the CBR reasoning model in order to imitate the human facilitator's thinking style. The proposed approach employs IBIS style that enables discussion participants to organize their opinions in a structure format. Experimental results demonstrated the ability of the proposed approach to facilitate positive and constructive discussions amongst several participants and to guide these discussions successfully towards consensus.

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