Pedagogical Agents as Team Members: Impact of Proactive and Pedagogical Behavior on the User

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ABSTRACT

In a virtual environment for the learning of cooperative tasks, learners have to coordinate with one or more autonomous agents in order to perform a task. This coordination requires that the human and agent team members reason and dialogue about their resources, action plans, and shared actions. This article proposes a new agent architecture called PC^{2}BDI designed to generate reactive, proactive, and pedagogical behaviors of the agents based on three agendas: the task, the dialogues, and the pedagogical scenario. An experimental study, in the context of learning a procedural activity in a virtual environment involving 3 team members (1 human and 2 agents), is presented to evaluate the effect of the agent behavior on a learner. The results show that using proactive pedagogical agents improves the learner's engagement and task learning.

Keywords

Human-Agent interaction, pedagogical agent, virtual environment

1. INTRODUCTION

In the context of a collaborative virtual environment (VE) for training and learning, coordination requires that team members, both humans and virtual agents, reason and dialogue about their actions, resources and shared plans [5]. However, coordination in such a context of mixed human-agent teamwork faces a number of issues. Firstly, one of the important characteristics to work in a team is that the team members proactively provide information by anticipating information needs of the other members [21] to maintain a state of mutual awareness. Furthermore, in a mixed human-agent team, agents provide pedagogical assistance so that the learners can reach their learning objectives. These pedagogical agents enable proactivity [27], learner's engagement in the VE for learning [14], and interaction among team members [19]. Secondly, the natural language communication among team members requires not only to take into account the current dialogue, but also the shared task and the beliefs of other team members [31]. Multiparty dialogues encourage group interaction and coordination among team

members. This advantage can be exploited to promote typical human activities such as (a) the learning in more social contexts and (b) the construction and maintenance of social relations between the members of a team.

During the last decade, several research projects have focused on designing agents in augmented VEs, their usage, their efficiency and limitations [4, 26, 33]. Some agents are developed and incorporated into VEs so that they appear more alive. Others possess limited but sufficient rationality, in order to increase the learners' involvement in VEs. However, these agents never possess both collaborative and pedagogical behavior to offer effective assistance to learners in the context of learning procedural activities in a task-oriented, mixed human-agent teamwork.

This article focuses on the task-oriented, collaborative and pedagogical behavior of agents in a VE designed to learn a procedural task. Multiparty dialogues between the user and pedagogical agents are exploited to improve the engagement in interactions and to proactively provide information needed by the user. Other aspects of embodied virtual agents, such as emotions and non-verbal communication are out of the scope of this article. In this context, we propose the (**PC^{2}BDI**) architecture of a pedagogical agent, that extends the (C^{2}BDI) agent architecture [3]. On the one hand, it allows the interleaving between deliberative and conversational (reactive and proactive) behavior for the realization of collective activities and information sharing among team members. On the other hand, it offers pedagogical behavior to provide appropriate assistance to the learner. An experimental study in the context of learning a procedural activity in a VE involving 3 team members (1 human and 2 agents) is performed to examine the effects of the behavorial capabilities of an agent on a learner.

In section 2, we present related work concerning existing agent architectures and pedagogical behavior of agents. Section 3 describes the architecture of the agents and their components. The evaluation of the effects of agent behaviors on the learner is presented in section 4 and the discussion on the results is described in section 5. Finally, section 6 summarizes the contribution and concludes the article.

2. STATE OF ART

Collaborative VEs for training allow learners to acquire new skills or knowledge that can be applied in real situations [14]. Some of the applications of these VEs include procedural task learning [26], decision-making during critical situations [38] and risk management training [4]. In VEs, the learners can perform activities accompanied by other users

or by virtual agents. These autonomous virtual agents, usually having some or all of the classic cognitive abilities such as decision-making, memory and planning are called Intelligent Virtual Agents (IVAs) [13]. They can also be Embodied Conversational Agents (ECAs), with a physical representation and able to demonstrate some human-like skills, such as face-to-face interaction, gestures, facial expressions, emotions and personality [9, 29]. Agents which can act as tutors or motivation vectors in a VE for learning are known as pedagogical agents [36]. Pedagogical agents can be linked to various cognitive theories [23], can have a natural interaction capability [9] and improve social engagement [16].

Several agent architectures exist that are potential candidates for designing collaborative and pedagogical agents in VE for learning[1]. For example, STEVE agent [33] developed on SOAR architecture, can explain and demonstrate the task to students and can work as the missing team member. However, there is only question/answer, but no dialogue management. Similarly, Paco agent [34] is built upon the collaborative discourse theory [32] and STEVE. It supports both collaboration and tutorial dialogues, however, it lacks of planning and deliberation capabilities. Other potential architectures for pedagogical agents can be IVAs or ECAs. Greta agent [29] is based on SAIBA framework, supports multimodal interactions between an agent and the user, and can improve the user's engagement. However, Greta also does not endow dialogue management and capability to collaborate. Finally, the C^2BDI [3] agent architecture is based on BDI model [30] that contains mental attitudes such as belief, desire and intention. The conversational behavior integrated in C^2BDI is based on the Information State (*IS*) [40] that contains contextual information about the current conversation. Furthermore, this architecture also supports multiparty interaction between a user and many agents. Similarly, Kopp and Pfeiffer-Lessmann also proposed an *IS* based interaction model for Max agent [24]. They considered coordination as an implicit characteristic of team members. These different agent architectures exhibit different capabilities and limitations. For example, the decision centric architectures mainly concerned with the planning and decision-making, where as dialogue management remains a major deadlock in IVAs [38]. Most of the existing embodied only integrates basic dialogue management processes. Thus, in the context of a collaborative VE for learning, neither decision centric not embodied architectures can be directly applied. Furthermore, these architectures do not allow to easily integrate a pedagogical behavior to the agent. Therefore, these agents cannot be directly used as pedagogical agents in the context of the learning of a task-oriented shared activity.

Pedagogical agents exhibit different characteristics: (a) they are adaptive [6], (b) they provide realistic simulations [33], (c) they address socio-cultural needs of learners [23], (d) they encourage learner's engagement and motivation [16] and (e) they improve learning and performance [14]. However, various studies conducted by Doering et al. [11], Choi and Clark [8], Schroeder et al. [36], and Veletsianos and Russell [42] concluded that these arguments are not always justifiable. For example, although Doering et al. [11] stated that the pedagogical agents are adaptive, they also noticed that firstly, in most cases these agents sometimes fail to

provide certain information in response to questions of the learner and secondly, they sometimes provide information inappropriately. Moreover, Choi and Clark demonstrated that simply adding pedagogical agents in a VE does not provide better results [8]. Indeed, the observed gain in user's learning is generally attributed to the pedagogy used by the agent rather than to the agent itself.

In addition, agent profiles based on reactive or proactive behavior also affect the overall performance of a learner in VEs [2]. Kim et al. [22] found that the pedagogical agents with visual appearance and communication capabilities give positive effects on learners. Although different aspects of an agent such as reactive, proactive and pedagogical behavior have been explicitly evaluated, the combined effects of reactive and proactive behaviors of an agent along with pedagogical behavior have not been evaluated. Schroeder et al., have concluded in their meta-analysis for the effectiveness of pedagogical agents for learning, that evaluation and comparison of pedagogical agents remain difficult because of their different roles, the complexity of interactions, different agent modalities, and the way experiments are designed for evaluation [36]. Thus, the use of pedagogical agents in virtual learning situations requires a thorough evaluation of the capabilities of the agents and of the opinions of the users.

To summarize, many different applications of collaborative VE for learning share common aspects in terms of *awareness* (consciousness and attention) of the human and agents team members [28], ability to share information [25], and effective team coordination [5]. Thus, it is important to take into account first, how team members (human and virtual agents) coordinate with each other, second, how they share their knowledge in order to establish common grounding and mutual awareness among them and third, how agents provide effective assistance to the learner. We propose an agent architecture that provides the deliberative and natural language interaction, as well as the pedagogical behavior to assist the learner in a collaborate VE for training. Similarly to Rich and Sidner [31], we are convinced that the dialogues can be managed in a deliberative way considering the collaborative task resolution in a human-agent teamwork. BDI-like architecture is a prominent choice, because it is based on the mental attitudes, and its procedural representation is close to the implementation. Concerning the evaluation, we aim to evaluate the effects of agent behaviors on the learner based on different aspects such as the engagement of the learner, learning gain, and the learner's opinions about the motivation of using virtual agents in a VE for learning.

3. THE PC²BDI AGENT ARCHITECTURE

The proposed Pedagogical Collaborative-Conversational BDI (PC^2BDI) agent architecture is a cognitive architecture that is inspired from the Belief, Desire, Intention architecture (BDI) [30], and in particular with its procedural implementation [43]. The collaborative and proactive behaviors of the PC^2BDI agent are built upon the joint intention theory [10], shared plan theory [15] and the theory of collaborative problem solving [44] along with the semantics of collective attitudes [12]. This architecture extends shared plan theory by introducing multiparty information sharing, anticipating the need of collaboration, and propositions for deriving natural language communication behaviors. PC^2BDI treats both deliberative and conversational behaviors uniformly as guided by the goal-directed shared

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[1]A number of pedagogical agents are discussed in Johnson et al. [20].

activity. It is based on the (C^{2}BDI) agent architecture [3] and adds a pedagogical layer to generate new behaviors.

3.1 Components of the Agent Architecture

The architecture is composed of four layers for interaction, accomplishment of shared activity and communicative goals, knowledge management, and pedagogical behavior (Fig. 1).

The interaction layer is responsible for the interface with the VE. It allows the agent to interpret the behavior of others in order to adapt its own behavior based on its decision-making process and on the dialogue manager.
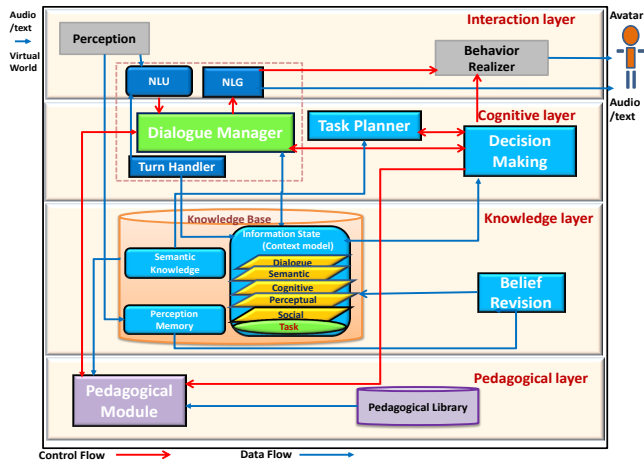

Figure 1: PC^{2}BDI Agent Architecture

The cognitive layer determines how the agent maintains collaboration with other team members. The task planner determines the appropriate actions by referencing the shared activities and the roles of each member. The decision-making process is motivated by the goals, plans, IS and semantic knowledge about the VE and the task. The multiparty Dialogue Manager (DM) [3] is founded on a model-based approach to interpret and generate natural language utterances relying on the current state of the IS. The DM classifies the intentions of received utterances and the proactive intentions determined by the decision-making, which can be associated to pedagogical primitives. It then passes the control to the pedagogical module. The multiparty turn-taking is derived from the Ymir architecture [39], using the angle and distance between the agent and the other team members, and his own intention to speak.

The knowledge layer manages the knowledge base that includes semantic knowledge, perceptual knowledge, and *IS*. Each agent shares the same semantic knowledge about the VE and shared activities in order to simplify the planning process. The IS contains contextual information about the current dialogue and about the current task, and the mutual beliefs shared among team members. The semantic modeling of the VE is based on the methodology for designing adaptive VEs for training proposed in [35]. This methodology provides distinct roles for design actors such as pedagogues (defining the pedagogical primitives), domain expert (describing the task model), designers (constructing VEs) and trainers (defining pedagogical scenarios).

The pedagogical layer brings the capability to provide assistance to learners either according to their demands or proactively by determining their needs. It uses the pedagog-
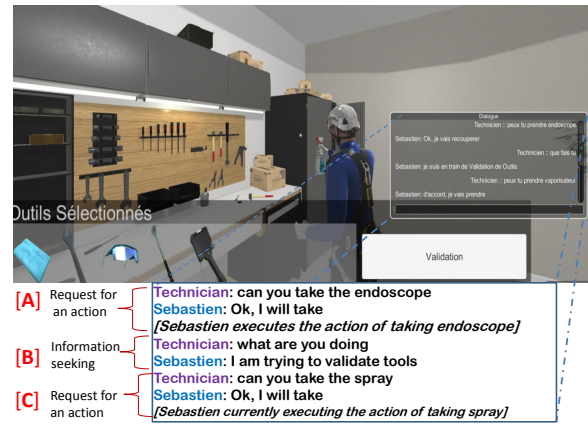

Figure 2: Reactive Conversational Behavior

ical actions described by the pedagogue to guide or correct the learner. It then passes the control to the DM to generate appropriate utterances and feedback when required.

3.2 Conversational Behavior of the Agent

Cooperation between a learner and accompanying virtual agents is supported through shared actions [10] and shared plans [15] that are synchronized through dialogues. The agent has both reactive and proactive dialogue capabilities that rely on the semantic modeling of the VE and task activities using the MASCARET meta-model [7]. Reactive conversational capabilities allow the agent to understand utterances and answer. Thus, the learner requests pieces of information to progress toward the goal. The agent can use all the knowledge contained in the different models with respect to the activities, roles, actions, resources and other objects in the VE, their properties and operations, to provide appropriate response. For example, in figure 2 [B], the learner asks about the current action of the technician Sebastien (information seeking). Moreover, the learner can also ask agents to perform certain actions during the task. For example, in figure 2 [C] the learner asks the technician to take the spray bottle.

The agent can also proactively communicate with other team members in order to establish or maintain cooperation, to satisfy the anticipated information needs of the learner or handle the sharing of resources. For example, in Fig. 3 [B], when the learner does not start her next action, the agent explicitly and proactively asks her to perform this action.

3.3 Pedagogical Behavior of the Agent

The agent plays different roles during the collective activity. Each agent can participate as an "equivalent" member of the team, and each agent can also provide the necessary pedagogical assistance to the user depending on the current context of the task. Pedagogical actions may be played by the agent or by the VE player directly. The pedagogical action library developed until now contains the following action categories: 1. pedagogical actions on the VE: *highlight an object, play an animation*, 2. pedagogical actions on user interactions: *change the point of view, block a position*, 3. pedagogical actions on the structure of the system: *describe the structure or an element of this structure; display an entity's documentation*, 4. pedagogical actions on the sys-

tem dynamics: *explain the objectives of a procedure, explain an action*, 5. pedagogical actions on the scenario: *display a pedagogical resource such as a video or text document, explain the objective of the current scenario*

The agent can assist the learner in one of the following conditions. Firstly, when the pedagogical action is explicitly specified by the teacher in a training scenario [35], the agent can then interpret this action in an appropriate primitive pedagogical action and pass control to the DM. Secondly, the agent may determine the information needs of the learner, or understand when the learner explicitly asks for information. For example, if the learner asks the agent "where is the endoscope?", the agent can highlight the endoscope and can provide the description of that object (see Figure 3 [C]). The agent can answer differently to the same question depending on the current context of the task and on the level of the learner (beginner, intermediate or expert). For example, if the learner repeatedly asks the same question about the endoscope, the agent can describe its operation, its different elements and in which actions it can be used. Similarly, if the current context of the task or the dialogue has been changed, the response to this query varies.
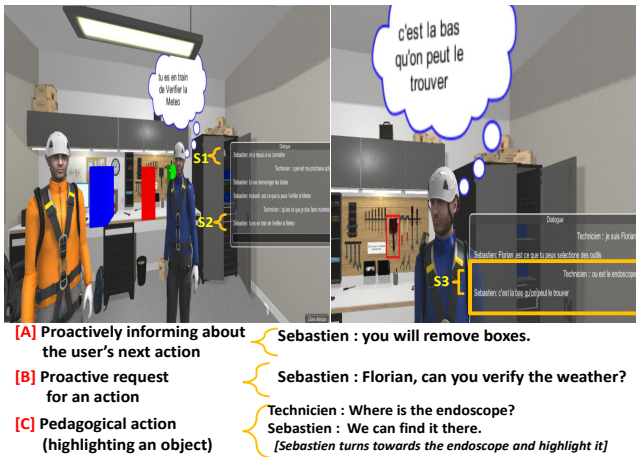

Figure 3: Proactive conversational behavior and pedagogical behavior: Highlight an object

The agent determines the need for pedagogical information of the learner according to the ongoing dialogue with the learner or via the actions performed by the learner. If the learner is a beginner, the agent can give information on the next action to be performed and resources to be used for this action (see Figure 3 [A] for instance). In addition, the agent identifies the need for assistance according to learners' behavior based on the number and types of errors made by user during previous actions. The agent classifies events generated by the learner into different categories (erroneous action and wrong resource as defined in [17]) depending on the current context of an activity. The agent then associates a pedagogical primitive appropriate to the type of event. This information is transmitted to the DM. The DM processes it and generates an utterance corresponding to the pedagogical action. For example, if the user makes "resource errors" and does not start the next action, the agent informs him about the next expected action and highlights concerned resources without being explicitly asked. If the user performs "action errors", the agent informs him about the next ex-
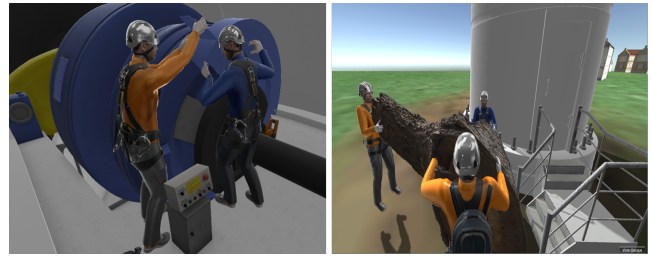

Figure 4: [A] Industrial scenario: Maintenance Activity, [B] Experimental scenario: Moving a trunk

pected action and how to perform it. Finally, if the user does not make any error, the agent only informs him about the action to be performed.

Discussion

This architecture has been integrated into a learning VE for the maintenance of a wind turbine. A PC^{2}BDI agent is associated to each virtual character. Figure 4 shows a screenshot of the maintenance scenario, where two technicians (an avatar of the learner and a virtual agent also playing the role of tutor) collaborate to perform a collaborative activity.

The originality of the proposed architecture, compared to "pure" BDI, lies first on the role of dialogues that modify together the believes, desires and intentions of the agent, and second on the collaborative nature of the agent's activity. Compared to the context model of Max agents, PC^{2}2BDI agent exhibits both reactive and proactive conversational behaviors, and explicitly handles cooperative situations through natural language interaction between team members taking into account the user in the loop. Like STEVE, PC^{2}BDI agent exhibits decision-making mechanism that allows the interleaving between deliberation, conversational and pedagogical behavior of the agent. Moreover, unlike Paco, the PC^{2}BDI agent also supports *IS* based task-oriented multi-party dialogue management capability. Furthermore, this approach consists in formalizing the conversational behavior of the agent related to the coordination of the activity and the support of the learner, which reduces the necessity to explicitly define communicative and pedagogical actions in the activity scenario.

4. EXPERIMENTAL EVALUATION

The objective of this experiment is to gain insight into the role of agent behaviors on the learner (user) in the context of a task-oriented collaborative activity in a VE for learning. To evaluate the effects of adding both proactive and pedagogical behaviors to the agents, we have considered two systems with different experimental conditions. These conditions are based on the reactive, proactive and pedagogical nature of agent behavior, and allow comparing the effects of reactive and proactive behavior along with the pedagogical behavior of an agent. In both conditions, autonomous virtual agents can work as equivalent team members with a learner in a collective activity. In the first condition, agents are reactive and can provide pedagogical information to the learner. However, they are not proactive, which means that they can react only on the user's initiative for the request of information or for the help to perform an action. In contrast, in the second condition, agents also exhibit proactive be-

havior and thus, they can determine the user's information need during the realization of a task and can provide help. Thus, agents can establish effective cooperation proactively during the shared task. In both conditions, these agents are endowed with the pedagogical behavior along with their dedicated reactive or proactive behavior in order to help the user to achieve their learning objectives.

We consider three aspects of evaluation which include (1) engagement and motivation of the learner, (2) task learning and (3) learner's opinion on the profiles of the agent. In order to evaluate these aspects, we have defined following three hypotheses:

- **Hypothesis 1**: By providing the pedagogical information during the procedural activity, the proactive agent improves the user's learning experience.

- **Hypothesis 2**: Subjects who begin the experiment with the scenario having proactive behavior of the agent have better results in terms of learning than those who begins with the scenario having only reactive agents.

- **Hypothesis 3**: The proactive pedagogical profile reduces the overall learning time.

4.1 Method

4.1.1 Participants

Since the VE's goal is to train students to a procedural task, a call was made through which 16 students from an engineering school in France were recruited. To ensure the consistency of the study panel, we imposed a controlled condition that the participants must be native French speaker. There were 11 men and 5 women between the ages of 19 and 23 years (mean 20.41 years, SD = 1.37).

4.1.2 Data Collection

In order to evaluate the impact of the behavior of the agent, several subjective and behavioral measures were used. Subjective measures are carried out using questionnaires in two parts (adapted from [37]). The first part is based on the user's engagement and commitment towards the shared tasks (Table 1) and the second part focuses on opinions of the user on the motivational behavior (Table 2).

Table 1: Questionnaire on the engagement and motivation towards the shared task

	Questionnaire
1	I was more attentive thanks to virtual agents.
2	Agents have been useful to me to learn the task.
3	I felt that agents encourage me to interact more with the VE.
4	I felt that agents encourage me to interact more with them.
5	Overall, agents helped me in my learning.

These subjective measures are complemented by behavioral measures to evaluate the learning process. These measures include the execution duration of actions, the total time required by the user to perform a task, the number of consultations for actions, the number of errors during an action, and the dialogue interaction between team members.

4.1.3 Procedure

The evaluation process involves three steps. In the first step before the experiment, participants were informed on

Table 2: Questionnaire on the user's opinion

	Questionnaire
6	Thanks to information provided by the agents, I was more motivated in my task.
7	I think that the interaction in natural language supports the learning activity.
8	The vocal capacity of the agents is important.
9	Collaborative VEs for learning are more interesting when accompanied by collaborative and pedagogical agents.

the general context of the activity to interact with virtual agents who are members of the team and about the general course of interactions, but no description of the procedure was given to participants. Figure 4 [B] shows a screenshot of the evaluation scenario where three technicians (an avatar of the learner and two virtual agents also playing the role of tutor) are collaborating to perform a collaborative activity. The scenario takes place in the workshop of a wind turbine company, where technicians present themselves to each other, discover their maintenance task, check if the weather is acceptable, remove obstacles, choose appropriate tools and reach the wind turbine (six sub-activities).

In the second step, participants are invited to perform experiments. In each experiment, there are three members of the team (an avatar controlled by the learner and two autonomous agents *Sebastien and Pierre* located in the workshop of a wind turbine company. Each participant is asked to perform experiments in one of the two sequences:

Sequence 1: (Exp1.1) Reactive + Pedagogical –> (Exp1.2) Proactive + Pedagogical

Sequence 2: (Exp2.1) Proactive + Pedagogical –> (Exp2.2) Reactive + Pedagogical

Subjects recruited to sequence 1 (Seq1) had to perform Exp1.1 followed by Exp1.2. Similarly, subjects enrolled in sequence 2 (Seq2) had to perform Exp2.1 followed by Exp2.2. Characteristics of agent's profiles are summarised in table 3.

Table 3: Characteristics of agent's profiles

Agent Profile	Characteristics of scenario
Reactive + Pedagogical	Virtual agents will have both reactive and pedagogical behavior
Proactive + Pedagogical	Only Sebastien will have both proactive and pedagogical behavior. Pierre will have pedagogical behavior. In addition, both Sebastien and Pierre exhibit reactive behavior.

After executing the scenario, participants fill the questionnaire on their experience (Table 1). The questions assessment is made on a Likert scale of 5 categories (1- strongly agree, 2- agree, 3- neutral, 4- disagree and 5- strongly disagree). After the end of the experimental sequence, the questionnaire on their opinions regarding motivation to the task and interaction with agents is filled (Table 2).

4.1.4 Design Analysis

In this study, since we have 16 participants (therefore 8 participants in each sequence), in order to obtain cumulative results, we decided to split the Likert scale in two groups (the first group with values of strongly agree + agree, and the second group with the last three scales). Given the multiple

dependent measures, we choose to use Fisher's exact test to calculate two-tailed value p. In addition, the result is also verified using the Chi-Square with Yates correction due to the small sample size (2×2). We also used the Student's test (t-test) to verify two-tailed hypothesis regarding the execution time of actions required by users. The significant level for all of the analysis was set to 0.05.

4.2 Results

The first experiment of each sequence is used to evaluate the effects of agent's reactive/proactive behavior on engagements of the learner as well as on the shared task.

4.2.1 Engagement of the Learner

We want to assess the engagement of the user from three points of views of user (attention, utility and encouragement for interactions). Figure 5 shows the reaction of users regarding their engagement with virtual agents in a VE.

The first question represents the learner's willingness in the group activity. By analysing the questionnaire, we found that only 13% participants in Exp1.1 have noted that they were more attentive because of virtual agents, while in Exp2.1, 88% participants felt that they were more attentive (Fig. 5). We have verified this result using statistical methods. The value of Fisher's exact test is p = 0.0101. We also confirmed the result by applying the Chi-Square approach (Chi-Square statistic is 9 and p = 0.0027), this result is significant at p <0.05. As the participants had no information about actions to be performed in the shared activity, information proactively provided by the agent absolutely sustained their learning. Consequently, the agent led learners to perceive their learning goals and thus complete their task.
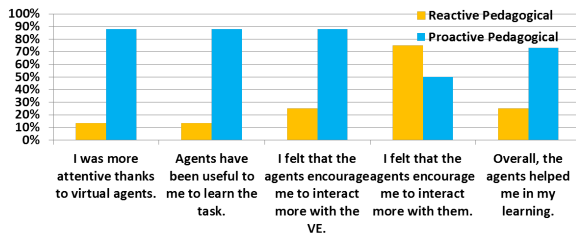

Figure 5: Engagement of the learner

The second question is related to the focus of the learner about the task. Only 13% participants in Exp1.1 found agents useful for learning, while 88% users in Exp2.1 found agents useful (Fig. 5). This result is significant at p < 0.05 as in the Fisher's exact test p = 0.0101 and Chi-Square statistic is 9 with p = 0.0027. The reason is that in Exp1.1 both agents are reactive, so they do not cooperate with the user and do not provide information without being asked. This explains that the users do not find them very useful. In the case of Exp2.1, one of the agents is proactive and therefore provide the necessary information.

The third issue concern the encouragement of learners to participate in the shared task. Only 25% of users in Exp1.1 found the agents encourage them to interact with the VE, while 88% of users agreed upon this point 5). This result is significant at p < 0.05 as in the Fisher's exact test p = 0.006993, and Chi-square statistic is 9.6 and p = 0.01946. The reason is that in Exp1.1 both agents are reactive, so they do not provide any information about actions and resources without being asked. However, in the case of Exp2.1, one

of the agent is proactive and can thus provide the necessary information to perform actions which henceforth motivates them to interact with VE.

These findings support hypothesis 1: by providing pedagogical information during the procedural activity, the proactive agent enhances the user's learning experience.

The fourth question concerns the encouragement of learners to interact with agents. 75% of participants in Exp1.1 agreed that the reactive agents encouraged more to interact with them, while only 50% of participants agreed in the second case (Fig. 5), in the Fisher test p = 0.363636 and Chi-Square statistics 1.0667 and p = 0.3017. This result is not significant at p < 0.05. This result is counter-intuitive: the user does not have information about the task, and in order to acquire this knowledge, she must interact with other team members to know about next actions to perform. However, in the proactive scenario (Exp2.1), the proactive agent can anticipate the user's information needs and provide information, even without request from the user. This result does not support the hypothesis 1.

Question five evaluates the overall contribution of pedagogical behavior of an agent on the learner's interaction in the VE (interaction with objects, other team members, and performing actions). 75% of users thought that the proactive pedagogical agents helped them in learning during the collective activity, while only 25% of users approved this fact in the reactive scenario (Fig. 5). The statistical value of Fisher's exact test is p = 0.040559. The statistical value of the Chi-Square is 6.3492 and p = 0.011743. This result is significant at p <0.05 and support the hypothesis 1.

The results show that hypothesis 1 is supported only in the first Exp2.1 because firstly, the agent can proactively provide the information required by the user to advance toward the goal and secondly, both agents can provide pedagogical assistance depending on the level of the learner. These characteristics motivate the learner to actively participate in the shared activity.

The statistical analysis on the execution time of actions required by users in the first experiment is done for the two sequences (Fig. 6 [A] [B]). Applying the Student's t-test for independent means, we get t = 1.18902 and p = 0.246064. The result is not significant at p <0.05. Although there was no significant difference between the execution time of these two activities, the total time required by the user to perform actions was higher in the case of reactive pedagogical scenario (in Exp1.1, mean execution time = 26.57 min, and in Exp2.1, mean execution time = 13.05 min). One of the reasons is that in the case of proactive pedagogical scenario, the communication cost (time) is higher than the reactive pedagogical case. Since, in the first experiment of the two experimental sequences, the user does not know the sequence of actions in advance, while in the case of proactive pedagogical scenario the agent provides pedagogical information to the user to advance the collective activity.

4.2.2 Task Learning

In this section, we study the effects of the order of experiments (Seq1:: Exp1.1 –> Exp1.2 or Seq2:: Exp2.1 –> Exp2.2) to evaluate the learning curve (time) between these two sequences. We firstly evaluated the learning gain with the first experimental sequence (reactive –> proactive) (Fig. 6 [A]). By applying the Student t-test for dependent means of the execution time of actions required by the user, we
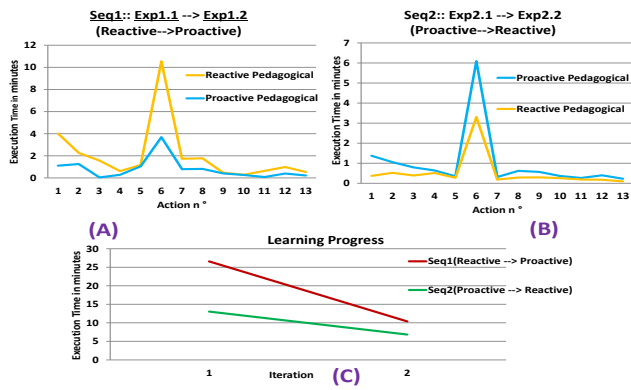
Figure 6: [A] Action Execution time required by the user in the experimental sequence Seq1, and [B] in Seq2, [C] Learning curve in both of the sequences

Figure 7: Opinions of Users

found that t = 2.123776 and p = 0.055163. This means that the result is not significant at p <0.05. However, the total time required by the user in the scenario Exp2.2 is significantly lower (mean time = 6.85 min) than that of the first experiment in the reactive mode. Furthermore, there was no significant difference between proactive experiences (Exp2.1 and Exp1.2). Total time required in Exp1.2 (mean time = 10.6 min) was lower than that of Exp2.1. This result supports one of the conclusions presented by Ganier, Hoareau and Tisseau [14] that the user learns the procedural actions in the VE by performing several times the same activity.

We now compare the time taken by the user to perform actions in the second experimental sequence (proactive –> reactive) (Fig. 6 [B]). By applying the Student t-test on these two dependent means we obtain t = 2.206821 and p = 0.047551. The result is significant at p <0.05. In addition, the total time required in the Exp2.2 (mean time = 6.85 min) was lower than that of Exp1.2 (mean time = 10.6 min).

With this result, we can conclude that learning is more efficient in Seq2 compared to Seq1. In other words, the use of proactive pedagogical agents in the initial phase improves the procedural tasks learning. We can therefore conclude that these results support the hypothesis 2 which states that subjects who begin the experiment with scenario having the proactive behavior of the agent have better results (in terms of learning), than those who begin with reactive agents.

In addition, we also noticed that although the experiments Exp1.2 and Exp2.2 are not significantly different (t = 0.77183 and p = 0.447749), the learning gain between the two experiments of each sequences was significant at p <0.05 (t = 1.7314 and p = 0.048109) (Fig. 6 [C]). These results support hypothesis 3 indicating that the proactive pedagogical behavior reduces the overall learning time.

4.2.3 Opinions of Users

We now evaluate the opinions of users regarding the motivation of using virtual agents in a VE for learning. Figure 7 shows the comparison of opinions of users on their motivation towards the task, the use of natural language and verbal ability and their overall opinion with respect to the utility of pedagogical virtual agents for learning.

We now analyse the results concerning the motivation of the learner to complete the collective activity (question 6). In both experiments, participants agreed that they were mo-
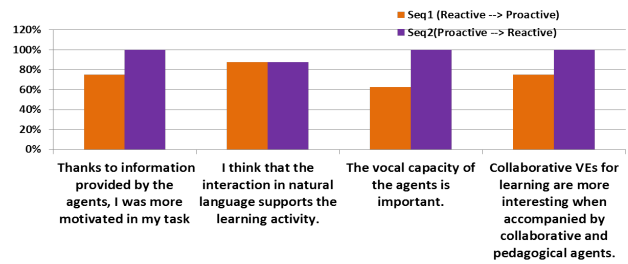
tivated to progress in the task thanks to the information provided by agents (Fig 7). Statistical analysis also supports the fact that there is no significant difference in their opinions (Chi-Square statistics is 2.2857 and p = 0.13057).

We can also conclude that the agent provides positive motivations and effects on learners through assistance and information. This conclusion may not be true for the evaluation requirements having only reactive agents such as in Exp1.1. These agents do not take initiative to share information. Nevertheless, if the learner requests, agents can provide information. Their behavior do not motivate and encourage learners to continue the shared activity. However, this conclusion is valid for the evaluation conditions of having proactive agent behavior such as in Exp2.1. Agents can engage in proactive way, and may establish and maintain collaboration within the team. Furthermore, information provided by proactive agents also encourage learners to actively participate in the shared task. Pedagogical agents provide help to reach the learning objectives as well as establishing and maintaining coordination among team members.

Questions 7 to 9 are interested in the personal view of the learner and to assess the importance of pedagogical behavior for learning (Fig. 7). There is no significant difference in the opinion that the interaction in natural language supports the learning activity (Seq1 83%, Seq2 83%). However, users in both experiments accepted that the verbal ability is important (as in Fisher exact test p = 0.2, the opinion is not significantly different at p <0.05). Users have agreed upon the fact (Seq1 75%, Seq2 100%) that VEs are more interesting for learning when accompanied by collaborative and pedagogical agents (Fisher exact test statistical value of p = 0.466667).

In addition, we analysed traces of dialogues between users and agents. The number of conversations initiated by the user was much higher (maximum 28, average 20) in Exp1.1 where both agents are reactive pedagogical, than that in Exp2.2 (maximum 12, average 9) where one of the agents is proactive pedagogical. Information search is faster with proactive pedagogical agents than with only reactive agents. The reason is that proactive pedagogical agents provide information needed by the user and reduces the possibility that the user asks for this information. However, in the case of having only reactive agents, the user must take initiatives to request information. In response, the agent can provide information or pedagogical assistance to progress the task. We also examined the traces of dialogue and observed that the user was more prone to interact with Sebastian in both the reactive and the proactive (73% of the user initiated dialogue interactions with Sebastien). The reason for this behavior is that in both scenarios, Sebastien introduced other members of the team with each others and also, Sebastian is

proactive in Exp1.2 and Exp2.1, which leaves the impression of providing information during the learning activity.

5. DISCUSSION

This study aims to analyse the effect of agent behaviors on the user to learn procedural activities in VEs. We tested three hypotheses. The first hypothesis states that by providing the pedagogical information during the procedural activity, the proactive agent improves the user's learning experience. This hypothesis was supported partly by the results. The results conclude that the users are more attentive with proactive pedagogical agents and found them helpful during the procedural task learning in VE. However, users felt that having only reactive agents encouraged them to interact with the agents. Furthermore, the results supported the second hypothesis stating that the users who begin the experiment with scenario having the proactive behavior of the agent have better results (in terms of learning), than those who begins with having only of reactive agents. Finally, the third hypothesis that the proactive pedagogical profile reduces the overall learning time is also completely supported by results.

One of the important findings is that participants were more engaged with the agent having a proactive behavior even if in each experimental sequence, both agents had pedagogical behavior. In addition, agents can provide pedagogical assistance according to the level of the learner. These characteristics motivate the learner to actively participate in the shared activity. The results also showed that proactive pedagogical agents have a higher impact on learning when participants have to learn the procedural task in collaborative VE for training. Participants who begin with the scenario having proactive agents required less number of consultations and less time to complete the task in the second trial than those who begin with the scenario having only reactive agents. These results are also consistent with the results in [14] on the procedural task learning phase in a collaborative VE for training and learning.

Proactive pedagogical behavior of the PC^{2}BDI agent also reduces the effort of complex scenario design. The PC^{2}BDI agent can produce pedagogical or communicative actions (a total of 2 * number of sub goals + number of sub goals where the first action is executed by an agent + number of sub goals not assigned to any particular agent + 2 * number of actions performed by the user) without being explicitly specified in the scenario. For example, without the PC^{2}BDI agent, a scenario (used in the experiment) with 6 goals where 1 goal is not assigned to any particular agent (by default, the user is supposed to achieve this goal), and 10 user operations, requires 33 communicative or pedagogical actions to be added manually by the domain expert or by the tutor [35]. Thus, the PC^{2}BDI agent architecture simplifies the design of scenario by providing communicative and pedagogical actions based on the current state of the activity and by taking into account the current mental state of team members.

Currently we have performed experiments with 16 engineering students. Although, the initial results and feedbacks are positive, it would be interesting to conduct evaluations with more participants in order to improve the precision of results. However, there are many improvements possible in the current system. For example, the pedagogical skills of the PC^{2}BDI agent remain fairly limited. This means for example, the agent can not overcome the negative actions of users. In other words, the consequences of actions performed by the user can not be restored by the agent. Furthermore, unlike STEVE agents [33], PC^{2}BDI agent does not have the capability of demonstrating the actions by doing it and then restoring all the effects back to the earlier state in the VE, so that the learners can perform the action to achieve their pedagogical objectives. In addition, the current implementation of the architecture does not support the replanning of the task scenario dynamically in case when the scenario cannot be continued because of the failure of certain actions.

A way to improve the the pedagogical agents is to adapt their behavior according to the performance of the learner. With this in mind, it is possible to integrate the implementation of the cognitive reliability and error analysis method (CREAM) [17] as well as the one in [41], so that agents provide more dynamic pedagogical behaviors.

Concerning the turn-taking capabilities of the agent, the participants mentioned that the movement of the head during the conversion was not realistic. The reason is that the turn-taking model in PC^{2}BDI architecture is not continuous and therefore depends on the response threshold value of each agent. It will be interesting to integrate more dynamic and continuous turn-taking behavior, such as that presented in [18], to provide a more natural interaction.

Another important remark is concerned with the limited natural language capabilities and the limited vocabulary for the agent. As we have previously specified, the natural language processing capacity of the PC^{2}BDI agent depends on the richness of the semantic description of the model. However, it would be interesting to integrate the modelling approach based on the data with the semantic modelling based approach. For example, the statistical approach based on dialogue corpus proposed in [1] can be used to find the most frequent dialogue patterns. These patterns can then be used to construct dialogue models in combination with the semantic modelling of VE [7] to provide more flexible and adaptable dialogue management capabilities.

6. CONCLUSION

The Behavioral architecture PC^{2}BDI proposed in this article provides to the agents the ability to coordinate their activities using communication in natural language. We then presented an experimental study to evaluate the impact of reactive/proactive pedagogical behavior of the agent on the learner in the context of the learning of a collective activity in a virtual environment involving three team members (1 human and 2 agents). The results show that the use of proactive pedagogical agents improves engagement and learning for the user. Proactive pedagogical agents have the power to convey information more accessible to other team members. The evaluation results indicate the significant difference between the two experimental sequences which includes sequence 1 (reactive pedagogical followed by proactive pedagogical) and sequence 2 (proactive pedagogical followed by reactive pedagogical) enable to perceive the usefulness of the proactive pedagogical agents. These results confirmed the initial anticipation that proactive pedagogical agents as equivalent team members and as tutors will be useful for collaborative learning in the VE.

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