Communicative Capabilities of Agents for the Collaboration in a Human-Agent Team

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***Abstract*—The coordination is an essential ingredient for the human-agent teamwork. It requires team members to share knowledge to establish common grounding and mutual awareness among them. In this paper, we propose a behavioral architecture *C^2BDI* that allows to enhance the knowledge sharing using natural language communication between team members. We define collaborative conversation protocols that provide proactive behavior to agents for the coordination between team members. We have applied this architecture to a real scenario in a collaborative virtual environment for training. Our solution enables users to coordinate with other team members.**

***Keywords*-Human interaction with autonomous agents, Cooperation, Dialogue Management, Decision-Making**

I. INTRODUCTION

In collaborative virtual environments (VE) for training, human users, namely learners, work together with autonomous agents to perform a collective activity. The educational objective is not only to learn the task, but also to acquire social skills in order to be efficient in the coordination of the activity with other team members [1]. Effective coordination improves productivity, and reduces individual and team errors. The ability to coordinate one's activity with others relies on two complementary processes: common grounding [2] and mutual awareness [3]. Common grounding leads team members to share a common point about their collective goals, plans and resources they can use to achieve them [2]. Mutual awareness means that team members act to get information about others' activities by direct perception, information seeking or through dialogues, and to provide information about theirs [3].

The collaboration in a human-agent teamwork poses many important challenges. First, there exists no global resource that human team members and virtual agents can rely on to share their knowledge, whereas, in a team of autonomous agents, the coordination can be achieved through the means of a mediator, or blackboard mechanism. Second, the structure of the coordination between human-agent team members is open by nature: virtual agents need to adopt the variability of human behavior, as users may not necessarily strictly follow the rules of coordination. In contrast, in agent-agent interactions, agents follow the rigid structure of coordination protocols (e.g., contract net protocol). Thus, the ability to coordinate with human team members requires to reason about their shared actions, and situations where team members need the coordination to progress towards the team goal. Moreover, another important characteristic of the human-human teamwork is that the team members pro-actively provide information needed by other team members based on the anticipation of other's needs of information [4]. Thus, in a human-agent team, agents should allow human team members to adjust their autonomy and help them to progress in their task.

The paper focuses on the task-oriented, collaborative conversational behavior of virtual agents in a mixed human-agent team. Other aspects of embodied virtual agents, such as emotions, facial expressions, non-verbal communication, etc. are out of the scope of this study. As the team members must have the shared understanding of skills, goals and intentions of other team members, we proposed a belief-desire-intention based (BDI-like) agent architecture named as *Collaborative-Conversational BDI agent architecture* (C^2BDI). On the one hand, this architecture provides the deliberative behavior for the realisation of collective activity and, on the other hand, it provides conversational behavior for the dialogue planning to exhibit human like natural language communication behavior for coordination. The contributions of this paper include: (1) the definition of collaborative communication protocols to establish mutual awareness and common grounding among team members; and (2) a decision-making mechanism where dialogues and beliefs about other agents are used to guide the action selection mechanism for agents to collaborate with their team members. The approach consists in formalizing the conversational behavior of the agent related to the coordination of the activity, which reduces the necessity to explicitly define communicative actions in the action plan of the agent. It also makes the human-agent interaction more adaptive.

In section II, we present related work on human-agent teamwork. Section III presents different components of our architecture. The conversational behavior is detailed in section IV. The next section illustrates how the solution fulfils the requirements of real educational scenarios. Finally, section VI summaries our positioning.

II. RELATED WORK

Both AI and dialogue literature agree upon the fact that to coordinate their activities, agents must have the joint-intention towards the group to achieve collective goal [5] and must agree upon the common plan of action [6]. The joint-intention theory specifies that agents have common intentions towards the group goal [5]. This theory does not guarantee that agents follow the same action plan. Comparing to this theory, the shared-plan theory [6] specifies that even agents share a common action plan to achieve the group goal, it does not guarantee that agents have the commitment towards the group to achieve that goal. Both of these theories are mainly applied for the coordination among a group of artificial agents. The C[2]BDI architecture takes the advantage of both of these theories to establish common grounding and mutual awareness among mixed human-agent team members.

A number of human-agent team models have been proposed in the literature [7], [8]. Collagen agent [7] is built upon the human discourse theory and can collaborate with a user to solve domain problems, such as planning a travel itinerary and user can communicate with agents by selecting the graphical menus. In [8], collaboration in teams is governed by teamwork notification policies, that is, when an important event occurs, the agent may notify the user with respect to appropriate modality and the user's position. To achieve collaboration between team members, [9] proposed a four stage model that includes (i) recognition of the potential for cooperation, (ii) team formation (iii) plan formation, and (iv) plan execution. Based on this model, [10] proposed an agent model and defines how collective intentions from the team formation stage are built up from persuasion and information-seeking speech act based dialogues, using motivational attributes goal and intention. Moreover, [11] proposed an agent based dialogue system by providing dialogue acts for collaborative problem solving between a user and a system. Recently, [12] have proposed a theoretical framework for proactive information exchange in agent teamwork to establish shared mental model using shared-plan [6].

One of the prominent approaches for dialogue modelling is the information state (IS) approach [13]. The IS defined in [14] contains contextual information of dialogue that includes dialogue, semantic, cognitive, perceptual, and social context. This model includes major aspects to control natural language dialogues. However, it does not include contextual information about the shared task. This leads to an incoherence between dialogue context and shared task in progress. In [15], an IS based interaction model for *Max* agent has been proposed that considers coordination as an implicit characteristic of team members. Comparing with [15], C[2]BDI agents exhibit both reactive and proactive conversational behaviors, and explicitly handle cooperative situations through communication between team members. Moreover, [14] proposed a taxonomy of dialogue acts (DIT++) based on the dialogue interpretation theory. The semantics of these dialogue acts are based on the IS based approach. This taxonomy was built mainly to annotate natural language dialogues. We are motivated to use it to understand and interpret conversation between human-agent team due to its following characteristics: (i) it is mainly used for dialogue interpretation in human-human conversation; (ii) it supports task oriented conversation; and (iii) it has become the ISO 24617-2 international standard for dialogue interpretation using dialogue acts.

III. C[2]BDI Agent Architecture

In this section, we describe components of C[2]BDI agent architecture that provide deliberative and conversational behaviors for collaboration (see Fig. 1). We consider that C[2]BDI agents are situated in an informed VE where agents can perceive entities and can access specific properties, such as the state, position, attribute values etc. of entities within their field

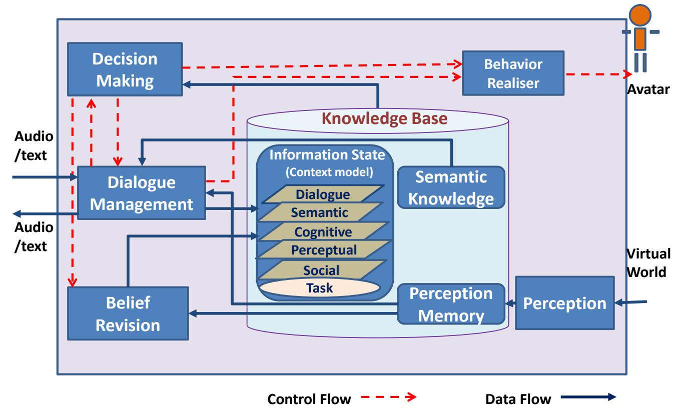

Figure 1: Components of Agent architecture and data flow

of perception. The agent architecture is based on the theory of shared-plan [6] and joint-intention [5].

The agent perceives the VE through the perception module. The current perceived state of the VE is an instantiation of concepts the agent holds in its semantic knowledge. The perception (in our case, multi-modal perception through vision and dialogue) allows agents to enrich their knowledge, and to monitor the progress of the shared activity. Agents have partial beliefs about the state of VE as they have limited perception. The belief revision specialises the classical belief revision function of BDI approach. Since, the state of the world can be changed due to an interaction by team members, the belief revision function periodically updates the knowledge base of the agent, and maintains the consistency of the knowledge base. The dialogue manager allows agents to share their knowledge with other team members using natural language communication. It supports both reactive and proactive conversation behavior, and ensures the coordination of the activity. The decision-making uses private beliefs and beliefs about others from the knowledge base to decide whether to elaborate the plan, identifying collaborative situations, to react to the current situation, or to exchange information with other team members. The behavior realiser module is responsible for the execution of actions and the turn taking behavior of the agent.

A. Knowledge Organisation

The organisation of knowledge in C[2]BDI agent allows to establish the strong coupling between decision making and the collaborative conversational behavior of the agent. The knowledge base consists of semantic knowledge, perception memory and IS. The semantic knowledge contains semantic information that is known a priori by the agent, such as the knowledge concerning concepts, and individual and shared plans. Following the shared-plan theory [6], C[2]BDI agents share the same semantic knowledge about the VE and the group activity. This simplifies the planning process of agents, as agents need to construct only their local plan. Moreover, sharing the same semantic knowledge also supports proactive conversation behavior of the agent as it allows the decision-making process to identify collaborative situations and information needed by other team members. The perception memory acquires information about the state of the VE perceived by the perception module, whereas, the IS contains contextual information about the current activity and dialogues.

B. Information State

The IS is primarily used in literature to control natural language dialogues [13], [14]. We extended its usage as the source of knowledge between the decision-making and conversational behavior of the C^2BDI agent to establish coherence between these two processes. In C^2BDI agent, the IS works as an *active memory* that contains beliefs and intentions of the agent. In C^2BDI agent, the semantic context of the IS is instantiated from concepts the agent holds in semantic knowledge, depending on the progress of the shared task. It includes the *agenda* that contains dialogue goals. These goals are added to the agenda due to communicative intentions generated by the realisation of the collaborative task and by the social obligations. To cooperate with other team members, the agent needs not only the information about the current context of the collective activity, but also beliefs about team members to establish common grounding and mutual awareness. To acquire these information, we extend the IS based context model of [14] by adding the *task context* to it (see Fig. 2).

The *task context* of our IS includes information about the *task* that contains intentions *task-focus*, goals, and desires of the agent. The C^2BDI agent follows the theory of joint-intention [5] to ensure that each team member has a common intention towards the team goal, therefore, the *task context* also contains *cooperative-information*, which includes beliefs about *group-goal*, *group-desire*, *group-intention*, *joint-goal*, *joint-desire*, and *joint-intention*.

We distinguish between the individual, group and joint intentions of the agent. The *group-goal* indicates that the agent knows that all team members want to achieve the goal at a time or another. Similarly, *group-desire* and *group-intention* can be defined analogously. For an agent a *group-intention* becomes a *joint-intention* when agents involved in its realisation expressed their mutual belief in this regard, i.e., when the agent knows that this intention is shared by other team members. To form a *joint-intention*, a necessary condition is that the agent must have individual intention to achieve this goal. Similarly, the semantics of joint-desire and joint-goal indicates that all team members have the same *group-desire* and *group-goal* respectively, and all team members know it. Thus, these shared mental attitudes in *task context* of an agent towards the group, specifies that each member holds beliefs about the other team members, and each member mutually believes that every member has the same mental attitude.

To cooperate with other team members, the *joint-intention* is not enough for an agent to engage in the realisation of collective actions. Rather, it only ensures that each member is individually committed to acting. The agent must also ensure the commitment of others to achieve this shared goal. Agents must communicate with other team members to obtain their *joint-commitments*. The agent has a *joint-commitment* towards the group, if and only if, each member of the group has the mutual belief about the same *group-goal*, the agent has the *joint-intention* about to achieve that goal, and each agent of the group is individually committed to achieve this goal. Thus, the shared belief of *task context* also includes the belief about the *joint-commitment* towards group to ensure that every team member has the commitment towards the group to achieve the shared goal. Hence, the IS not only contains information about the current context of the dialogue, but also that of the collaborative task, i.e., beliefs about other team members potentially useful for the agent for its decision-making.

Dialogue Context	agent-dialogue-acts, addressee-dialogue-acts, dialogue-act-history, next-moves	
Semantic Context	agenda, qud, communication-plan, beliefs, expected-dialogue-acts	
Cognitive Context	mutual-belief	
Social Context	communication-pressure	
Perception Context	object-in-focus, agent-in-focus, third-person-in-focus	
Task Context	cooperative-info	group-goal, group-desire, group-intention joint-goal, joint-desire, joint-intention, joint-commitment
	task	task-focus, goals, desires

Figure 2: Extended Information State in C^2BDI architecture

IV. Conversational Behavior

The conversational behavior allows C^2BDI agents to share their knowledge with other team members using natural language communication, and ensures the coordination of the team activity. The agent interprets and generates the dialogues based on the semantics of dialogue acts proposed in [14]. To achieve the coordination among team members, we propose *collaborative conversational protocols* for the agent. These protocols construct the *conversational desires* for the agent which, when activated, result in *conversational intentions*.

A. Collaborative Conversational Protocols

As we want the agent to be proactive and cooperative, we have defined three collaborative conversational protocols (CCPs). These protocols ensure the establishment of the collaboration among team members to achieve the *group-goal*, and its end when the current goal is achieved. Every team member participating in a collaborative activity enters in the collaboration at the same time, and remains committed towards the group until the activity is finished.

a) CCP-1 : When the agent has a new *group-goal* to achieve, it communicates with other team members to establish *joint-commitment*, and to ensure that every team member use the same plan to achieve the *group-goal*.

When the agent has one or more *group-goals* to achieve, and if it has no mutual belief about them, it constructs *Set-Q(what-team-next-goal)* dialogue act and addresses it to the group. By addressing this open question, the agent allows both users and other agents to actively participate in the conversation. If the agent receives the choice of the goal from another team member, it adds a mutual belief about *group-goal* and *group-intention* to its *cognitive context*, and adds the belief about *joint-goal* to the *task context*. It then confirms this choice by sending a positive acknowledgement (by constructing *Auto-feedback(positive-ack)*) to the sender.

When the agent receives *Set-Q(what-team-next-goal)* and has no mutual belief about *group-goal*, i.e., no other team member has already replied to the question, it can decide to reply based on its response time. It chooses one of the available goals based on its own preference rules, and informs sender by constructing *Inform(team-next-goal)* dialogue act. When the agent receives positive acknowledgement from one of the team members, it modifies its IS by adding mutual belief about *group-goal* and *group-intention*, and belief about *joint-goal*.

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If the agent has *joint-goal*, but not *joint-intention* to achieve this goal, the agent needs to ensure that every team member will follow the same plan to achieve *group-goal*. If the agent has more than one plan to achieve this goal, it constructs *Choice-Q(which-plan)* act and addresses it to the group, or if the agent has only one plan for the goal, it constructs *Check-Q(action-plan)* act addressing to the group. When the agent receives a choice of the plan, or the confirmation of the choice of a plan, it adds *joint-intention* to its *task context*. It confirms this by sending a positive acknowledgement, and constructs the belief about *joint-commitment*. When the agent receives *Choice-Q(which-plan)* or *Check-Q(action-plan)*, and has no mutual belief about *group-intention*, it constructs *Inform(plan-choice)* or *Confirm* dialogue act respectively to inform about its plan selection. When it receives positive acknowledgement from one of the team members, it adds individual- and joint-commitment to achieve the group-goal.

b) CCP-2 : When the agent has performed all its planned actions of the shared activity, but the activity is not yet finished, the agent requests other team members to inform him when the activity will be finished.

The agent generates *Directive-request(inform-goal-achieved)* to ask other members to inform it when the activity will be finished. When the agent receives this dialogue act, it adds communicative goal *Inform(goal-achieved)* to its agenda.

c) CCP-3 : The agent who finished the last action of the shared activity, informs other team members that the activity is terminated.

The preconditions for CCP-3 are that the agent believes that it has performed the last action of the collaborative activity, and it has the *joint-commitment* to achieve *group-goal*. If these preconditions are satisfied, it constructs *Inform(activity-finished)* dialogue act addressing it to the group. When the agent receives the information that the last action of the activity has been finished, and has the belief about *joint-commitment* in its *task context* and has a communicative goal *Inform(goal-achieved)* to achieve (due to CCP-2), it constructs *Inform(goal-achieved)* dialogue act to inform other team members that the goal has been achieved. It then adds the belief about the achievement of the goal, and removes the corresponding intention from the *task context*. When the agent receives the information about goal achievement, it removes the corresponding intention from the *task context*, and drops the communicative goal *Inform(goal-achieved)* if it has.

The agent waits for certain time (until the threshold of its reaction time is expired) and if no team member has already replied, the agent can create an intention to reply. Otherwise, the agent simply listens to the conversation and updates its beliefs. Thus, in order to establish mutual awareness and to coordinate with other team members, the agent participates in the conversation. Once agents have established the *joint-commitment*, they can coordinate with other team members to achieve the *group-goal*. These protocols are instantiated when the decision-making identifies collaborative situations that satisfy necessary conditions to be fulfilled. These situations add expectations of information from other team members, which need to be satisfied. In a human-agent team, the user's behavior is uncertain, i.e., a user may not necessarily follow these protocols. As the agent updates their beliefs using perception information, which can make expectations to be true from the observation of actions of user perceived by the agent, or from the information provided by other team members. This mechanism makes these protocols robust enough to deal with uncertainty about user's behavior. One of the advantages of these protocols is that the dialogues for the coordination need not to be scripted in the definition of action plans.

B. Decision-Making

In C^2BDI agent, decision-making is governed by the information about current goals, the shared activity plan and knowledge of the agent (IS and semantic knowledge). The decision-making algorithm is shown in Algo. 1. The algorithm

Algorithm 1 DECISION-MAKING ALGORITHM

```
Require: IS
B = IS.SemanticContext.Belief
D = IS.Task-Context.Desire
I = IS.Task-Context.Intention
agenda= IS.Semantic-context.Agenda
while true do
    update-perception(ρ) and Compute B, D, I
    Π ⇐ Plan(P, I )
    while !Π.empty() do
        if agenda is not empty or the agent has received an utterance then
            Process Conversation-Behavior()
            Compute new B, D, I
            Π ⇐ Plan(P, I )
        if the task-focus contains communicative intention then
            Process Conversation-Behavior()
        Identify-Cooperative-Situation in the current shared plan Π
        if Cooperative-Situation is matched then
            Process Conversation-behavior()
        α ⇐ Plan-action(Π), execute(α)
```

verifies whether the agenda in IS is not empty or *task focus* contains communicative intentions. If so, control is passed to the conversational behavior that supports the natural language communication. Otherwise, the agent chooses the plan to be realised. If agent identifies some cooperative situations in the collective activity, where the agent can not progress without assistance, i.e., if the preconditions for one of the CCPs are satisfied, then the control is passed the to the conversational behavior. The cooperative situations generate communicative intentions in the agenda, which causes the agent to interact with other team members to share their knowledge. The agent updates its IS if the control is passed to the conversational behavior, and deliberates the plan to generate the intention. Once the intention is generated, the agent selects actions to be realised and, in turn, updates its *task focus* in IS to maintain the knowledge about the current context of the task.

V. IMPLEMENTATION

This section shows how the C^2BDI architecture has been applied to a collaborative VE for learning of a procedure for industrial maintenance. We illustrate, through a real educational scenario, how decision-making and dialogues allow an agent to coordinate its actions with those of the learner.

A. The Educational Scenario

This scenario describes a maintenance procedure in a plastics manufacturing workshop. The scenario consists in the replacement of a mould in a plastic injection moulding machine (see Fig. 3). This specific intervention requires a precise coordination of tasks between two workers: the setter and the machine operator. The use of autonomous agents allows the learner to execute the learning procedure.

Figure 3: Collaborative realisation of the maintenance procedure in the virtual environment.

Let's consider a situation in which both the user (playing the role of an operator) and the virtual agent (playing the role of a setter) want to replace the mould (see Fig. 4). Following sequence of dialogues describe a typical interaction between them.

A1 : Agent : *What should we do now?* [Set-Q(team-next-goal)]
U1 : User : *We should replace the mould.* [Inform(team-next-goal)]
A2 : Agent : *Ok.* [Auto-feedback(positive-ack)]
A3 : Agent : *Should we use the mould replacement plan?* [Check-Q(action-plan)]
U2 : User : *Yes.* [Auto-feedback(positive-ack)]
.
.
(Agent executes "verify-circuit" action.)
A10 : Agent : *Inform me when you will finish the activity.* [Directive-request(inform-goal-achieved)]
(User executes "lock-the-door" action.)
U8 : User : *What should I do now?* [Set-Q(next-action)]
A11 : Agent : *You have to lock the door.* [Answer(next-action)]
U9 : User : *I have locked the door.* [Inform(action-done)]
A12 : Agent : *We have succeeded to replace the mould.* [Inform(goal-achieved)]

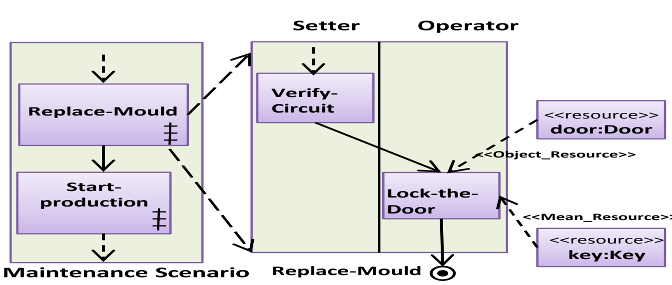

Figure 4: Partial view of the action plan shared between Setter and Operator.

At the beginning, both, the user and the virtual agent have a goal *Replace-Mould*. From the semantic knowledge about the activity, the agent identifies that this goal is shared between team members (in this case, with the user), the goal becomes the group-goal. Table I shows a subset of the agent's knowledge. The agent has a group-goal as Replace-Mould in the IS, but does not have the mutual belief about it. The decision making process identifies this collaborative situation that fulfils conditions of CCP-1 (see Algo. 1, line 15). The CCP-1 generates *Set-Q(team-next-goal)* dialogue act, and adds the communicative intention to the agenda in IS and thus, generates natural language utterance *A1*. When the agent receives utterance *U1*, it interprets *U1* as *Inform(team-next-goal)* dialogue act. As the agent has the same group-goal, it generates positive acknowledgement *A2* for the user and creates mutual-belief about the Replace-Mould (Table II). Now, to ensure that the user will follow the same action plan, the agent constructs *Check-Q(action-plan)* dialogue act considering that the agent has only one plan to achieve group-goal Replace-Mould, and generates *A3*. When the agent receives positive response *U2* from the user, it constructs the joint-intention as well as a joint-commitment to achieve the goal and updates the IS. Now, the decision making process deliberates the plan and computes the new intention (Algo. 1, line 18). Let the current intention of the agent be to *Verify-Circuit*. The subset of agent's knowledge is shown in Table III.

After executing the last action "Verify-Circuit" by the agent from its plan, and as the shared activity is not yet finished, it utters *A10* following CCP-2. The agent interprets the utterance *U8* as an information seeking *Set-Q(next-action)* act, which adds an intention *Answer(next-action)* in its agenda in IS. The decision making process transfers the control to the conversational behavior as the agenda is not empty (see Algo. 1, line 9). By performing the introspection in its shared plan, the agent finds the next action of the user and utters *A11*. Once, user informs the agent that he has finished the last action "lock-the-door" of the shared plan (*U9*), the agent informs that the goal is achieved (*A12*) following CCP-3.

TABLE I: SNAPSHOT OF IS FOR AGENT BEFORE APPLICATION OF CCP-1

	Role R_1 (agent)
Information State	*Task-Context*(group-goal("Replace-Mould"))

TABLE II: SNAPSHOT OF IS FOR AGENT AFTER ESTABLISHING JOINT-GOAL

	Role R_1 (agent)
Information State	*Cognitive-Context*(mutual-belief (group-intention("Replace-Mould") group-goal("Replace-Mould")); *Task-Context*(group-goal("Replace-Mould") joint-goal("Replace-Mould"))

TABLE III: SNAPSHOT OF IS FOR THE AGENT AFTER ESTABLISHING JOINT-COMMITMENT

	Role R_1 (agent)
Information State	*Cognitive-context*(mutual-belief(group-intention("Replace-Mould"); group-goal("Replace-Mould")); *Task-Context*(group-goal("Replace-Mould") joint-goal("Replace-Mould") joint-intention("Replace-Mould") joint-commitment("Replace-Mould") taskFocus(Intention("Verify-Circuit") Intention("Replace-Mould")))

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B. Integration with Virtual Agent

The C2BDI architecture has been integrated with the interaction model for virtual and real human [16] on the GVT platform [17]. The behavior realiser module interacts with the associated virtual agent, and sends requests to it, to perform actions chosen by the decision-making module or by the dialogue manager (turn taking behavior). The user interacts with VE by controlling his avatar thanks to a tracking system of the body and hands. Furthermore, the platform has also been enriched by a voice interface system that uses voice recognition and synthesis of Microsoft (see Fig. 5)].

Figure 5: View of the collaborative scenario with one user.

In C2BDI architecture, the natural language understanding (NLU) and generation (NLG) is based on the rule based approach [18]. When the agent receives an utterance, it uses NLU rules to determine the corresponding dialogue act type, and the dialogue contents are identified using the semantic knowledge and the contextual information from the IS. The dialogue manager processes these dialogue acts. When the agent has the communicative intention, it constructs dialogue act moves, and NLG rules are used to generate natural language utterances corresponding to the dialogue act.

VI. Conclusion

The proposed behavioral architecture C2BDI endows the agents in the collaborative VE with the ability to coordinate their activities using natural language communication. This capability allows users and agents to share their knowledge with their team members. The architecture ensures the knowledge sharing between team members by considering the deliberative and the conversation behaviors, not in isolation, but as tightly coupled components, which is a necessary condition for common grounding and mutual awareness to occur. The collaborative conversational protocols we proposed enable agents to exhibit human-like proactive conversational behavior that help users to participate in the collaborative activity. While the implemented scenario already shows the benefits of the solution, the behavior of the agents could be enriched both in terms of collaborative team management and in terms of natural language dialogue modelling. Particularly, it would be interesting to endow agents with problem solving capabilities to select their communicative intentions, or to engage themselves into information seeking behaviors and negotiation rounds, as observed in human teamwork [19].

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