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A SITUATION-BASED MULTI-AGENT ARCHITECTURE FOR HANDLING MISUNDERSTANDINGS IN INTERACTION

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During interactions, system actors may face up to misunderstandings when their local states contain inconsistent data about a same fact. Misunderstandings in interaction are likely to reduce interactivity performances (deviation or deadlock) or even affect overall system behavior. In this paper, we characterize the misunderstandings in interaction between system actors (that may be human or systems' agents) in interactive adaptive systems. To deal with such misunderstandings and to ensure state consistency, we present agent-based architecture and scenario structuring approach. The system includes several agents devoted to scenario unfolding, plot adaptation and consistency management. The scenario structuring is based on the notion of *situation* that is an elementary building block dividing the interactions between systems' actors into contextual scenes. This pattern not only supports the scenario execution, but the consistency management as well. In order to organize and control the interactions, *situation* contextualizes system's actors interactions and activity. It also includes prevention and tolerance agent-based mechanisms to deal with the misunderstandings and their causes. We validate our consistency management mechanisms using Uppaal simulation and provide some experimental results to show the effectiveness of our approach on an Online Distance Learning case study.

Keywords: Interactive adaptive systems; misunderstandings in interaction; situation structuring; consistency management

1. Introduction

In interactive systems, as games and simulators, users and the internal agents can modify system content and progress in real time through input adjustments. The interactive systems may adapt system execution not only to user's actions, but also to user's profile and behavior, making these systems adaptive. In order to perform the adaptation, the system must capture users' behaviors from their interactions. Then, according to system's and designer's logics, it adjusts its execution to what it perceives of user's logic. Due to user's actions unpredictability, the execution process of an interactive system is also not predictable.

One of the important problems in interactive systems is the potential misunderstanding between the users and the system and more generally between system's actors, virtual system's agents or physical human users. If the system does not capture correctly or confuses user's actions, or if the users do not understand what the system expects, that may lead to an erroneous interpretation of their behavior and an erroneous adaptation of system execution. This misunderstanding may concern user-system interactions, but it can also appear in any kind of interaction between any system's actors. It may be due to the incomplete actors' data or the non-determinism of actors' behavior and cause the interaction deadlock or application failure.

In our recent work, (Pham *et al.*, 2011; Trillaud *et al.*, 2012), we have defined the *misunderstanding in interaction* as: *when two or more system's actors have incoherent data in their local visions about the same fact f and these data is used during their interaction, that can cause an interaction deviation from the planned scenario*. An actor may be human user or virtual system's agent. The local vision is actor's own knowledge about its external world (virtual environment, system's resources...), its relations with others actors (subset of their states) and its own profile (internal state). So, our work focuses on the management of the consistency between the actors and the system and between actors' local visions in order to handle the potential misunderstandings in interactions.

To handle misunderstandings we propose to structure the application's execution into interaction sequences called *situations* and including misunderstanding prevention and tolerance mechanisms. Each *situation* corresponds to a contextual resource-centered sequence of activities and events and is characterized by preconditions and postconditions. That allows the system to control the execution and to establish the causal links between the *situations*. This model confines actor's interactions in a given context in order to control their execution and manage the consistency. Consistency handling mechanisms, are inspired by techniques from

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dependability domain (Laprie *et al*., 2004) since there is an analogy between the misunderstandings in interactive systems and the errors handled in fault tolerant systems. To use this situation-based scenario structuring, we conceived agent-based system architecture (Pham *et al*., 2013) that allows system's scenario to be represented by *situation* combination and uses agent components to control system's execution, scenario unfolding and consistency management. The architecture includes two kinds of agents: i) agents representing system's actors that either interact with the user(s) or with each other (as no-player characters in games) and ii) system's control agents involved in system's execution. Some of these control agents are involved in the consistency management by tracking and handling the misunderstandings in interaction between system's actors.

We have evaluated our consistency management approach and mechanisms through simulation. First, we have used Uppaal[1] model to validate the consistency management mechanisms inside the situations blocks from the actors' interactions point of view. This allows to assess the structural properties of our overall execution model for consistency management during the interactions. Then, we performed experimentation using GAMA simulation platform[2] on Online Distance Learning case study in order to show the effectiveness of misunderstanding in interaction handling.

In what follows: section 2 presents the related work in the domain of the interactive systems architectures for consistency support. In sections 3 and 4 we formalize the misunderstandings in interaction from our point and view and present their handling mechanisms. Sections 5 and 6 describe our system's architecture and the situation-based structuring. The consistency management model is validated using Uppaal in section 7 and its effectiveness in section 8. Section 9 concludes the paper.

2. Related work

In the recent research, we can find several works dealing with the user-system dialogue where the communication is done through a real human language (Karsenty and Botherel, 2005; Lopez-Cozar *et al*., 2010; Rapaport, 2003). According to (Rapaport, 2003), negotiation is the key to understanding: a cognitive agent understands by negotiating with the interlocutor or by hypothesizing the meaning of an unknown word from the context. This agent can negotiate with itself on something external by comparing its perception and its internal knowledge in order to correct its own misunderstandings. Other works propose to use confidence scores to measure the reliability of each word in a recognized sentence (Jiang, 2005). Besides, (Lopez-Cozar *et al*., 2010) proposed to implement a frame correction module, independent of speech recognizer. This module corrects misunderstandings in a sentence, caused by the errors in speech recognition, by replacing the incorrect frame with an adequate one. (Karsenty and Botherel, 2005) applied the adaptable and adaptive transparency strategies in the TRAVELS to help the users to understand and react appropriately to system rejections and misunderstandings. The ability of making system's interpretations explicit and informing the users on how to correct misunderstandings are two ways to help users handle them. This strategy is very effective in misunderstanding detection and raises the rate of appropriate user responses after system rejections. All of these works deal with the problem in speech dialogue where the misunderstandings are the more frequent. But the misunderstanding can be found in other forms of interaction like actions, gesture...

Our purpose is to define how we can treat the misunderstandings between the actors themselves besides the user-system misunderstandings. It is not easy to recognize such class of misunderstandings. In the dependability domain (Laprie *et al*., 2004), we find the inconsistency problem between systems and operators. The *automation surprise* is inconsistency error occurring when the system behaves differently than its operators expect (Combefis and Pecheur, 2009). It may be due to a mismatch between the actual system behavior and the operator's mental model of that behavior (King, 2011), and it can lead to *mode confusion* and even to critical failures. In general, misunderstandings come from the gap between user's logic and designer's logic, all along action planning between the actors.

Many works, particularly in interactive storytelling, have been done to solve the mismatch between users' behaviors and system logic (Magerko and Laird, 2004; Young *et al*., 2004; Barber and Kudenko, 2008; Paul *et al*., 2011; Silva *et al*., 2003) by predicting the user's future actions and detecting the invalid ones that deviate the execution from the planned objectives.

Minemsis architecture (Young *et al*., 2004) uses a mediator to detect when the player is attempting to execute an action that may threaten the integrity of the story plan. This approach doesn't aim to alternate the story but to incorporate unplanned actions or avoid them. Besides, IDA (Magerko and Laird, 2004) introduces a specific agent called *Director* to maintain the story line. It also predicts player's actions to determine if they may endanger the plot and to try to avoid them before they happen. If there is a problem, the *Director agent* can alter the world context by changing any accessible parameter in application's world's state.

In PAPOUS (Silva *et al*., 2003), the story to be told is organized in levels and each level consists of a set of *StoryBits* characterized by different properties, characters

[1] http://www.uppaal.org/
[2] https://code.google.com/p/gama-platform/

and events. PAPOUS manages the inconsistency between a virtual storyteller and the audience decisions in a simple way: the storyteller ignores missing or inadequate inputs and chooses the next *StoryBit* according to previously narrated one or to story desirability.

In an interactive system, we try to build the less constraining environment to the users actions. But, the higher is the degree of freedom the application allows, the more easily users's actions may deviate from the planned scenario and the more easily misunderstandings may occur. GADIN (Barber and Kudenko, 2008) is an interactive text-based system using story goal regeneration mechanisms in order to change the game goals into new ones when the player's actions move too far away from the planned goal state.

MIST (Paul *et al.*, 2011) has another approach to deal with the scenario deviation problem. It attempts to repair stories that are already in progress when they are invalidated by unforeseen events. The preemptive detection of invalid plan steps is done in advance some close steps before the point of failure. Once an invalid step is detected, the story management tries to substitute the story plan by a consistent one.

In general, prediction approaches are costly. For instance, the short-term player behavior modeling module implanted in (Magerko and Laird, 2004) creates an entire copy of the whole world's state. This module simulates the world changes according to user's actions. This kind of approaches seems not well suited to a real-time interactive systems, nor to systems where user's behavior cannot be easily modeled by a set of rules.

Our approach focuses on software and component design model integrating misunderstandings prevention and handling mechanisms. It relies on 3 points: the system observes and analyses users' and system's states, detects the misunderstandings or their consequences and acts to keep the consistency between actors before and at the end of interaction sequences. These mechanisms do not try to predict users' behaviors but take into account users' states to adapt system's execution in order to avoid misunderstandings between system's actors.

3. Misunderstandings in Interaction

We define a *context* as *a set of informations that can be used to characterize the situation of an entity* (Dey, 2001) where an *entity* is an actor involved in the interactions and may be represented by a system agent. A *situation* is an interaction sequence between several actors or agents in a shared fixed context. Thus, an interaction during system's execution is carried out between at least two actors within a common context.

3.1. Context and Actor's Local Vision. The context is related to actor's activities (Hommel *et al.*, 2000; Dourish, 2004; Picard and Estraillier, 2010). There is interdependence between the common context and the actors located in this context. An actor performs its activities depending on the current situation and the available contextual information. Each actor has to observe and to perceive the world, to interpret it with its own logic, to combine the new information with its existing knowledge in order to obtain its own contextual vision and to update its current knowledge as shown in Fig. 1. This knowledge is called the actor's *local vision*.

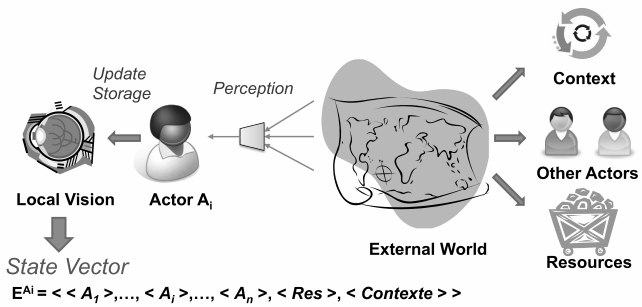

Fig. 1. From the external world to the actor's local vision

The *local vision* is actor's own knowledge about the external world (environment, resources...), the relations with other actors (other actors' states), and its own profile (internal state). For an actor A_i, the local vision is a state vector E^{A_i} (as depicted in Fig. 2). This state vector is hierarchical and divided into sub-vectors corresponding to states of every system's actors $A_1, A_2, ..., A_n$ (with n the number of system's actors), including A_i's own state vector, resources state vector Res and context state vector $Context$. Each sub-vector can be divided again into lower level sub-vectors related to actors' component entities. For instance, the element A_1 may be a sub-vector composed of m elements that can be other smaller sub-vectors or a final data value corresponding to an end-level attribute: $< A_1 >=< A_1^1, A_2^1, ..., A_m^1 >$ The division into sub-vectors is done until the chosen granularity is reached.

$$\mathbf{E^{A_i}} =<< \mathbf{A_1} > ... < \mathbf{A_i} > ... < \mathbf{A_n} >, < \mathbf{Res} >, < \mathbf{Context} >>$$

$$\begin{aligned}
&< A_1 >=< A_1^1, A_2^1, ..., A_m^1 > \\
&\qquad < A_1^1 >=< A_1^{11}, A_2^{11}, ..., A_m^{11} > \\
&\qquad ... \\
&\qquad < A_m^1 >=< A_1^{1m}, A_2^{1m}, ..., A_m^{1m} > \\
&< A_i >=< A_1^i, A_2^i, ..., A_m^i > \\
&... \\
&< A_n >=< A_1^n, A_2^n, ..., A_m^n > \\
&\qquad < A_1^n >=< A_1^{n1}, A_2^{n1}, ..., A_m^{n1} > \\
&\qquad ... \\
&\qquad < A_m^n >=< A_1^{nm}, A_2^{nm}, ..., A_m^{nm} > \\
&< Res >=< R_1, R_2, ..., R_p > \\
&< Context >=< C_1, C_2, ..., C_q >
\end{aligned}$$

Fig. 2. Local vision for an actor A_i as a state vector

Each state vector contains data elements representing the knowledge perceived by the corresponding actor and characterizing the involved entities. Moreover, it must be underlined that all sub-state vectors $< A_1 >, < A_2 >, ..., < A_n >$ except $< A_i >$ are the results of A_i's perception, so they are partial. It means that these vectors do not contain the whole real state of the corresponding actors $A_1, A_2, ..., A_n$. However, the vector $< A_i >$ contains its own state that is supposed to be complete.

3.2. Misunderstanding Definition. The local vision allows to an actor to be able to interact with the others with strategy and coordination. But, the local vision is not static, it evolves during interaction sequences. The perceived data is not always identical between different actors due to their differing perceptions and local environments. Hence, their local visions may become inconsistent during the interactions. That can lead to a different interpretation of a same fact (a sentence, an action, a state...). If the actors use this inconsistent data in future interactions, a misunderstanding may arise.

We give the following definition in (Pham *et al.*, 2011): *Two actors are in a misunderstanding state when: i) they are in interaction with each other, ii) there is incoherent data in their local visions about the same fact and iii) this data is used during the interaction. A fact is considered as objective data or absolute reference to system's actors or resources states*. If we consider the interactions between two actors as acts of language, the misunderstanding can be observed when two actors think that they talk about the same thing whereas they actually talk about different subjects (Rapaport, 2003).

We formalize this definition as follow: let two actors A and B interacting in the presence of the fact f from the external world. State vectors E^A and E^B are the local visions of A and B. The atom E_f^{real} is the absolute reference to f. The knowledge perceived by A and B about the fact f is represented by the atoms E_f^A and E_f^B. From state vector point of view, these atoms can be a sub-state vector or a data value element of E^A and E^B: $E_f^A \subset E^A$ and $E_f^B \subset E^B$

The perception can be seen as an internal action that cannot be observed by other actors and corresponding to the local vision updates after having performed or observed an action. The perception of A and B about f in Fig. 3 is represented by two following formulas:
$A : E_f^{real} \longrightarrow E_f^A$ and $B : E_f^{real} \longrightarrow E_f^B$

Misunderstanding in interaction appears when E_f^A is different from E_f^B: $E_f^A \neq E_f^B$

Hence, the local visions of A and B are incoherent. The distance D_f^{AB} measures the difference level between E_f^A and E_f^B: $D_f^{AB} = |E_f^A, E_f^B|$

The ideal misunderstanding free situation is when the perception of A and B on a fact f is identical: $E_f^A = E_f^B$

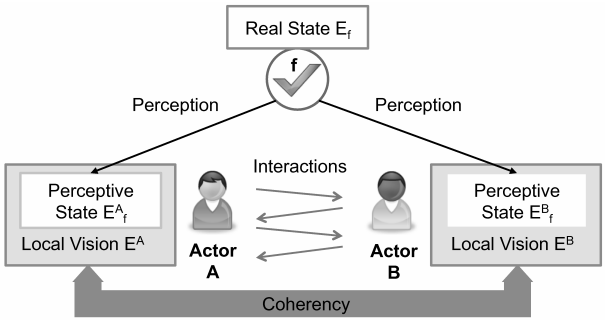

Fig. 3. Actors A and B perceive the fact f in interaction

and the distance $D_f^{AB} = \emptyset$

3.3. Elements that Cause Misunderstandings. Misunderstandings in interaction have various causes:

Different References It happens when interacting actors have different contexts. The interactions between actors are carried out under a concrete context that influences their behaviors. The actors located in different reference worlds will consider different things. For instance: the word "bug" is a kind of insect but in the computer world it refers to an error or a fault that produces an incorrect program execution. If the interaction context differs, actors' local visions will not be synchronized and misunderstanding conditions may be established.

Different Logics The actions of an actor depend on his own logic and deduction rules. For example: two actors interact about the identity of some "old person". For A, an old person means a person over 60 years: old(x) $\Rightarrow$ age(x)>60year. For B, "old person" means the oldest known person: old(x) $\Rightarrow \forall y$ age(x) $\geq$ age(y). If B asks A for an old person, B will expect the oldest person, whereas A will just provide someone old but not especially the oldest one. If B asks again, A may provide different answer and A and B will be in a misunderstanding since each actor has his own logic.

Semantic Ambiguity The wrong interpretation during the interactions can bring to a different perception. Semantic is internal (Rapaport, 2003), the external world is reflected subjectively in actor's "mind" that creates its own narrow knowledge. It is obvious that an actor can interpret as correct or wrong a fact because of the lack of information or the imperfection of the observation. For instance: in an e-learning application, a camera has to check student presence. Due to the limited camera scope, a student may be warned because of his absence, whereas he is still there but out of the camera scope.

3.4. Misunderstanding Consequences. Misunderstandings in interaction have also various outcomes.

Interaction deviation The interaction chain between two actors diverge from the planned scenario. An actor can estimate incorrectly the state of its interaction partners because of misunderstandings. As result, the actor will make a wrong decision based on the wrong observed state of its partners. Instead of an appropriate action according to the planning, the actor's behavior will diverge from its normal logic and from the logic of other interacting actors.

Interaction deadlock This problem arises when the misunderstanding is revealed and the actors get stuck in the middle of an interaction sequence. In this case, an actor receives an answer or a demand that he does not expect, because he is expecting some others reaction. The interaction sequence will be broken. Both actors (or at least one of them) do not know what to do any more.

Propagation If the misunderstanding is not detected or revealed, it can be propagated along the scenario and the execution of the application. The inconsistent data are not treated and remain for forward interactions. Furthermore, the misunderstanding severity may increase.

4. How To Manage Misunderstandings

The aim of misunderstanding management is to avoid misunderstanding occurrence as much as possible. If the misunderstanding happens anyway, it should be eliminated. Moreover, before the misunderstanding is detected, the interactions between two actors may have already deviated from the planned scenario. We must intervene to synchronize their data and their behaviors.

4.1. Necessary Occurrence Conditions.

A misunderstanding may occur during an interaction sequence if:

C1 *Actors' presence*: at least two actors participate in the interaction sequence. The misunderstanding occurs only when actors interact with each other.

C2 *Inconsistency of local data*: the knowledge about a same fact f is totally different or contain a part of different data. There is data inconsistency in the actor's local visions.

C3 *Data Sharing*: inconsistent data is used as shared information or common contents between the actors during their interactions.

If the three conditions are met, the misunderstanding will occur. Otherwise, it is not possible. For instance, if two actors have inconsistent data but they never interact with each other (*C2* is satisfied but not *C1*), the misunderstanding will not arise. Moreover, the actors may have different data about a same fact, but if they do not use it as shared data during the interaction (*C1* and *C2* but not *C3*), they will not face misunderstanding.

4.2. Approaches.

We classify the misunderstanding management into four classes:

Ignoring If the misunderstanding is minor, we can just ignore it. This is similar to the Ostrich Algorithm (Tanenbaum and Woodhull, 2006) in deadlock treatment.

Prevention Misunderstanding occurrence can be prevented by denying one of the three necessary conditions mentioned previously. If one condition is missing, we remove the possibility of misunderstanding occurrence. Actors' local vision should not contain inconsistent data. Ideally, their knowledge should be identical and coherent all along the interaction. Hence, actors' data consistency should be checked after each interaction sequence and synchronized if needed. Moreover, shared data should be identified before interactions begin. An explicit declaration of the shared data allows actors and system's control agents to check the consistency of this data before the actors use them. If an inconsistency is detected either the data is synchronized between the concerned actors or isolated to avoid its use during the interactions.

Tolerance Aims to detect latent (potential) misunderstanding during the interaction and resolve it when it is revealed (i.e. when it becomes effective). Misunderstandings are similar to the threats (fault, error, failure) affecting system service in the dependability domain (Laprie *et al.*, 2004). For instance, the byzantine or inconsistent failure happens when some or all the system users perceive differently service correctness. *Automation surprise* and *mode confusion* occur when the system behaves differently than its users expect (King, 2011). These examples show the effects of different actors' perceptions. The principles of misunderstanding tolerance are similar to the fault-tolerance with error detection and system recovery. The implemented mechanisms track down the system service deviation, and put the system into degraded mode or restoration. We suggest adapting fault-tolerant techniques to misunderstanding management in interactive applications by: i) regularly check actors' local vision data in order to detect and to eliminate both latent (potential) and revealed (effective) misunderstandings, if possible, before interaction deadlock; ii) resolving interaction deviation or deadlock by appropriate handling mechanism: either the system rollbacks to a misunderstanding free state in order to retry the last interaction or it goes on but with reinforcement actions synchronizing actors' threads, but in the most transparent manner for the user and with respect to the designer's storyline.

Removal Refers to misunderstanding detection and elimination. It is mainly achieved using regular coherency control to detect misunderstandings ant data synchronization to eliminate them.

4.3. Handling Solution. To handle misunderstandings in interaction, we explore two directions: adaptability structure and fault tolerance. Our solution relies on three points: i) we build robust system architecture with specific additional agent components that are in charge of misunderstandings in interaction management; ii) we organize the scenario and the system execution using *situation* blocks that are not only the basic narrative construction elements but also the execution patterns that contextually confine the interactions; iii) we integrate into situations' dynamic execution the consistency management, including data synchronization, misunderstanding detection and treatment inspired and adapted from fault-tolerance techniques. Hence, we structurally prevent from a part of potential misunderstandings before each interaction sequence start and guarantee misunderstanding free state at its end.

In the following sections, we present and detail these 3 contributions of our research.

5. Proposed Agent-Based Architecture

Several architecture models for interactive systems have been proposed according to the specific purpose of each work. We chose the approach of multi-agent system in (Sehaba *et al*., 2005) as a starting point to build our model. The advantage of this approach is that each agent can be organized and work autonomously and strategically. We define 4 system control agents (Fig. 4 shows the overall architecture).

Observer agent: It observes user's behaviors and state, formalizes, normalizes and transfers them to the scenario agent.

Scenario agent: It makes decisions about scenario orientation according to user's state, planned scenario and permanent objective defined by the designer. This agent tries to find the best way to orientate the application execution. It takes charge of the library of *situations* planned by the designer. The *situations* (defined in section 6) represent scenario components and are the interaction and the activity sequences that can take place in the application as, for instance, all possible scenes in a theatre play.

Director agent: This agent receives the decision taken by the *scenario agent*. He takes in charge the production of the adaptive scenario and realizes a modification, an answer or an action adapted to the users.

Script agent: Its task is to track and handle the inconsistency in 3 steps: i) *Detection*: detect, confine or partition the inconsistency between situation's actors in order to identify the causes of the misunderstanding; ii) *Treatment*: apply the handling mechanism or strategy to remove the inconsistency and to correct the deflected state that causes the incoherence; iii) *Evaluation*: estimate the efficiency of the treatments in order to improve the applied mechanism for the next time.

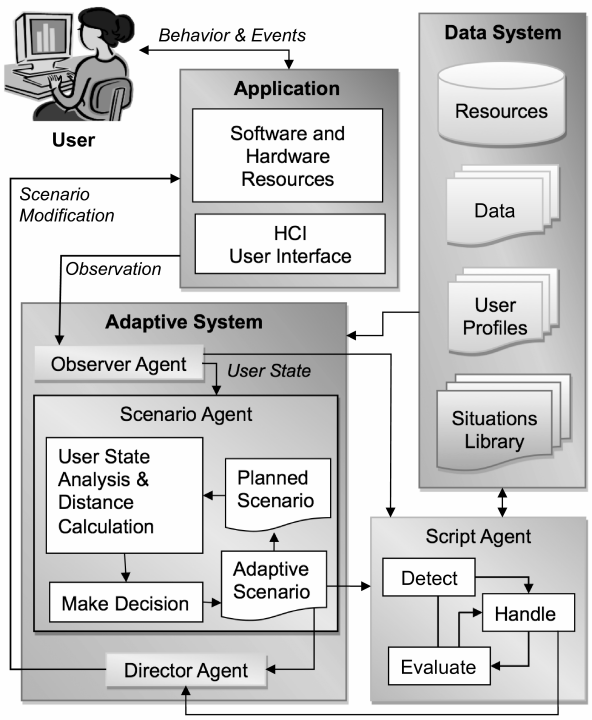

Fig. 4. General agent-based architecture for interactive system

6. Situation-Based Scenario

6.1. Interactive storytelling approach. Interactive storytelling is the unfolding of a story that the user's decisions impact (Champagnat *et al*., 2010; Lebowitz and Klug, 2011). It defines how to generate scenarios which are both interesting and coherent. We consider that the interactions in an interactive application can be organized, strongly or weakly, as a story scenario. That allows us to adapt ideas from storytelling domain to organize the interactions.

The scenario in interactive storytelling is represented by a series of actions/events linked together by cause and effect (Karlsson *et al*., 2006) or by ordered link (Magerko and Laird, 2004; Silva *et al*., 2003) or by Hierarchical Task Network planning (Paul *et al*., 2011) where each task is decomposed into subtasks until the primitive actions. But these scenario structuring approaches are not suited to build complex interaction sequences where the user's actions are free, non predictable and depending on a great amount of context data. Hence, we propose the notion of *situation* that can be seen as a scene encompassing not only interactions execution but also interactions management and resources use. The *situations* are the basic narrative elements that facilitate

interactions' planning and management by characterizing, contextualizing and confining them.

6.2. Situation Model for Scenario Structuring. The interactions are split into a set of situations. Each situation is a sequence of interactions between two or more actors in a precise context to achieve a predictive objective. It is characterized by (Fig. 5): pre-conditions, post-conditions, a set of participating actors and a set of resources. Since actors' behavior, especially for human actors, are not always precisely modeled, and due to the influence of external events, the progression of a situation can be considered as an execution and adaptation black box where the interactions are executed in a non-predictable way. A situation also includes consistency management. It represents a set of mechanisms devoted to the prevention, detection and treatment solutions, in order to redress and adjust situation's progression in spite of misunderstanding and inconsistency problems. Consistency management is carried out all along the situation progression from the local context initialization to the post-conditions completion.

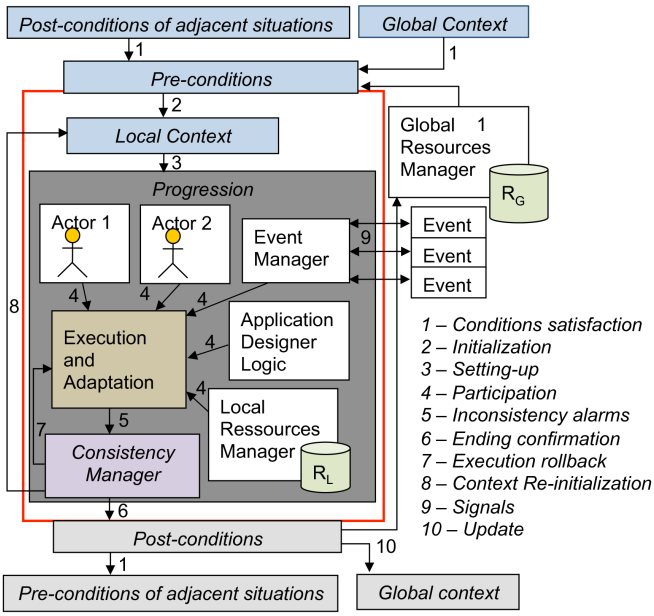

Fig. 5. Elementary Situation Structure

6.3. Situation Graph and Application Execution. The situations are considered as the plot structuring elementary blocks. Each application provide a set of situations defining all the possible interaction sequences that can happen during the application execution. They can be grouped and linked together in order to build the overall application scenario. The scenario is then represented by a directed graph of situations. Each node is a situation and each edge is a transition from one situation to another. The situations graph shows the causal relationships between scenario situations. A scenario may have several beginnings and also some possible endings (for instance, Fig. 10 in section 8 depicts the situation graph of the presented case study).

The situation-based scenario approach improves the execution control and interaction adaptation. The application progression becomes a scenario unfolding from one starting node to one final node on the predefined situation graph (taken in charge by the *Scenario agent* in the global architecture). If more than one situation is possible, the most pertinent one will be chosen by the *Scenario agent*. To increase the adaptability, we can avoid the definition of a predefined graph. In that case, the situation's choice is made according to the pre-conditions that best satisfy the global state and decision criteria. This method is flexible, adaptive, and applicable in real time during application execution, but it can lead to uncontrollable situation order or infinite loop, if the post-conditions and pre-conditions do not contain sufficient data. To avoid this issue we add a specific situation that handles the absence of post/pre-condition matching when necessary (Pham *et al.*, 2011).

7. Consistency Management Model

Handling Mechanisms The consistency management that we propose consists of a set of specific methods, techniques and mechanisms that aim to handle the misunderstanding problem and to obtain data consistency all along the interactions. They are similar to the dependability techniques (Laprie *et al.*, 2004).

Prevention mechanisms try to suppress misunderstandings occurrence conditions in order to avoid misunderstandings. To avoid data inconsistency, the proposed technique is the explicit declaration of all involved data before situation's interaction sequence start. It aims to identify and share actors' local visions in order to decrease the possibility of interaction deviation. If inconsistency is detected in the collected data the actors perform data synchronization. This synchronization is also done during the interaction sequence in order to avoid the inconsistency of data newly perceived.

Tolerance mechanisms guarantee interactions' continuation despite misunderstanding occurrence.

Misunderstanding detection: regular check of i) the shared data used during the interactions and ii) the deviation between actors' logics.

Interaction recovery: once a misunderstanding is detected, the system apply one or several of the following techniques: i) *rollback* brings the system back to a previous misunderstanding free state to retry the interactions; ii) *rollforward* brings the system to a new

misunderstanding free state from which the interactions will go on; iii) *reinforcement* requires from one or from several participant actors to do some additional interactions.

Removal mechanisms involve misunderstanding detection and correction, followed by *reinitialisation* of the last interactions, or of the whole interaction sequence. The detected misunderstandings are diagnosed to determine their causes: which data are inconsistent? which ambiguities exist in the interaction context? are there protocol faults? An appropriate correction method is then applied to eliminate the related misunderstanding. Finally, the interactions are restarted from the last stable point or from the beginning.

7.1. Inside the Situation Structure. Our situation based architecture allows the integration of the previous misunderstanding management mechanisms inside the situation in order to control the misunderstandings and their consequences all along situation execution. We define three phases:

Prologue phase: Before interactions start, actors local visions are synchronized through the explicit declarations of interaction content and data. If the initial data of involved actors are identical, the possibility of misunderstanding occurrence will be reduced. If the inconsistency exists, a negotiation step is performed between the inconsistent actors. Then, either one or several of them will modify their data, or the divergent data will be isolated/removed and not considered during the interactions.

Interaction or Dialogue phase: when the interactions are carried out, the actors will update their local data, step by step, as they continuously observe and perceive each other. Despite the initial local vision agreement, misunderstanding may nevertheless occur during interactions. This is why their local shared knowledge is synchronized all along the interaction sequence in order to avoid that local data about same facts diverge in actors' local visions. One or several techniques of *reinforcement, rollback, rollforward* should be used.

Epilogue phase: All the interactions are done in the previous phase. If the post-conditions are fulfilled, we can exit the situation with the expected results. But if, for some reason, we do not reach the expected post-condition, the *Script agent* has to detect and settle the existing incoherency in order to avoid the propagation of the misunderstandings to other situations. The system may also require that actors perform reinforcing interactions, or, if necessary, make a rollback to a last known stable state, which necessitate a regular state saving mechanism. If it is not possible, a restart of the whole situation should be done. The main goal of this phase is to exit the situation with the appropriate post-conditions and without latent or active misunderstanding. But, the rollback or reinforcing interactions may not lead the actors towards the planned post-conditions. Thus, we add in the situation model a special exception exit point that allows the current situation to be stopped without expected post-conditions and that leads to *exception handling situations*.

7.2. Formal Validation in Uppaal. In order to validate the proposed solutions and verify system's important properties after consistency mechanisms integration, we model our overall proposition using Uppaal modeling and simulation tool (Behrmann *et al.*, 2004). We aim to check what properties are preserved after the consistency mechanisms integration. Hence, we model a simple case where the scenario is composed of two situations that have the same behavior and the actors are considered from the consistency management point of view. This is a structural validation of system's behavior. When the number of situation increases, we shall, additionally, check the situation chaining and scenario validity. In (Dang *et al.*, 2013), we show how to use the Linear Logic to achieve this on a entertainment case study. Hereafter, we focus only on the structural validation.

7.2.1. Element Modelling. The model of our system contains five parts: i) 3 models devoted to actor's different aspects (internal behavior, communication channels and its local vision); ii) the situation block model that integrates the three-phase misunderstanding handling mechanisms; iii) the scenario model of the scenarized application execution presented as a succession of two templated situations. The communication between Uppaal models is done through message exchange (sending/receiving).

Actor Models. In order to represent actor's processes and state, we conceive three automata:

ActorLogic (Fig. 6 (left)) represents actor's behavior logic by 4-action loop (Observe, Evaluate, Decide, Act). If the actor receives wrong messages, the bad data may disturb its evaluation, its decision and its activities and may lead to its blocking. To handle inconsistent data, a synchronization state (**Sync**) is added to check actor's local vision before the normal activity loop.

ActorMessenger (Fig. 7 (left)) is the communication part devoted to the data perception from messages sent by other actors. The perception results may be the states **Expected**, **Lost** or **Unexpected**. It influences actor's actions.

ActorInternalStates (Fig. 7 (right)) describes actor's internal state: **Nominal** if nothing goes wrong or **non-Nominal** if actor's action is blocked. According to these two states, different mechanisms of consistency management can be realized: recover, rollforward, exception treatment or restart.

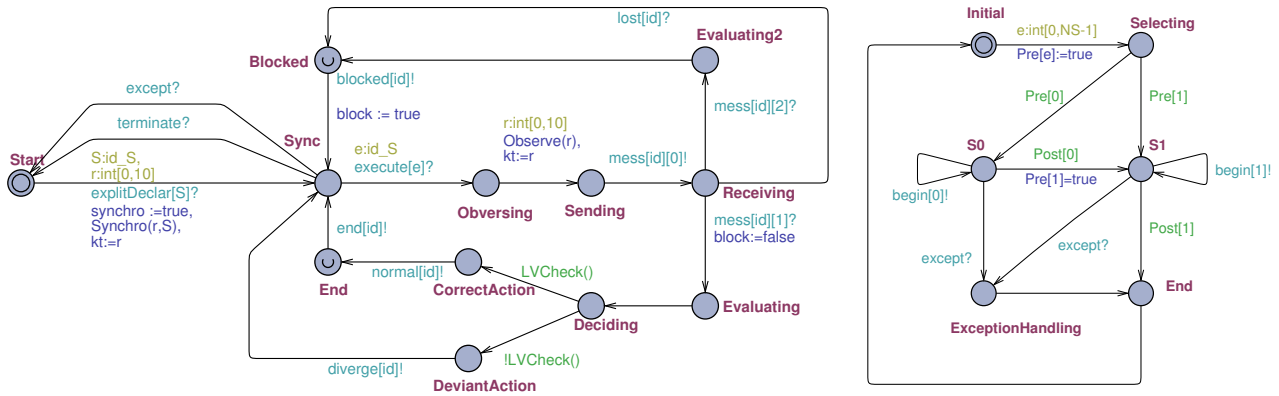

Fig. 6. Actor Model (left) and Scenario Model (right).

These three automata describe actors activity and interaction including misunderstanding occurrence and consistency management.

Situation Model. The *Situation* model (Fig. 8) represents the situation's three-phase progress including misunderstanding handling mechanisms as described in section 7.1. This model is devoted to situation's dynamic and presents different global states and transitions. We do not distinguish which transition is carried out by which agent among all system agents and actors of the general architecture (Fig. 4). In particular, the Dialogue phase is split into two states: **Execution** corresponding to interactions between participant actors and **Consistency** corresponding to consistency management where *Situation* automaton has to supervise actors' actions states from *ActorLogic* automaton: **CorrectAction**, **DiviantAction** or **Blocked**. Depending on these states, different mechanisms will be selected and applied.

Scenario Model. Application execution is in fact a succession of transitions from one situation to another. This process is divided into two steps: choice of the next situation and execution of the chosen situation. To model this execution, we built *Scenario* automata where the scenarion is composed of two situations S0 and S1 as shown in Fig. 6 (right). **Selecting** location refers to decision state, locations **S0** and **S1** correspond to the execution of the defined situations. In this model, we suppose that the decision mechanism is based only on the satisfaction of situations' preconditions. The transition from **Selecting** to **S0** (or **S1**) represents the chosen situation launching. Once this transition is done, *Scenario* automaton sends an authorization message to the *Situation* automaton in order to start situation's execution. When the pos-tconditions of the executed situation are fulfilled, either the next situation is launched, or the automaton stops at the **End** location. If *Scenario* automaton receives the message *except* from the current situation, it will move up to the **ExceptionHandling** state and then finish anyway at the **End** final state.

Communication between models. Fig. 9 summarizes the communication between the five automata of our global simulation model. The arrows refers to sending/receiving messages by the automata. *Scenario* automata stays at the highest control level and triggers *Situation* automata. Interactions between actor's three models are triggered or modified by the consistency management messages of the *Situation* model.

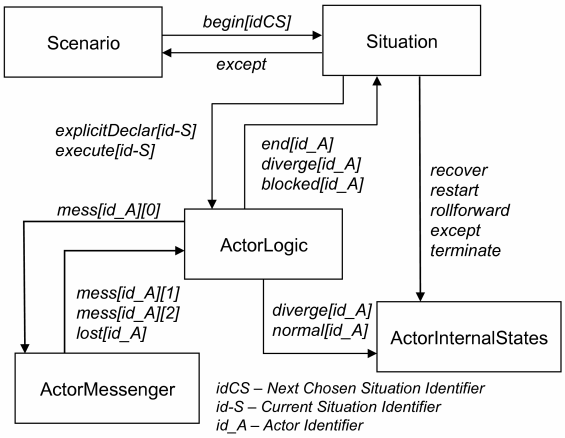

Fig. 9. Exchanged Messages between models

7.2.2. Properties Validation. The toolkit Uppaal supports not only an automata conceiving editor, but also a simulator to run the system and a verifier to model and check several system's properties. We will check our model for three properties: reachability, safety and the absence of deadlock.

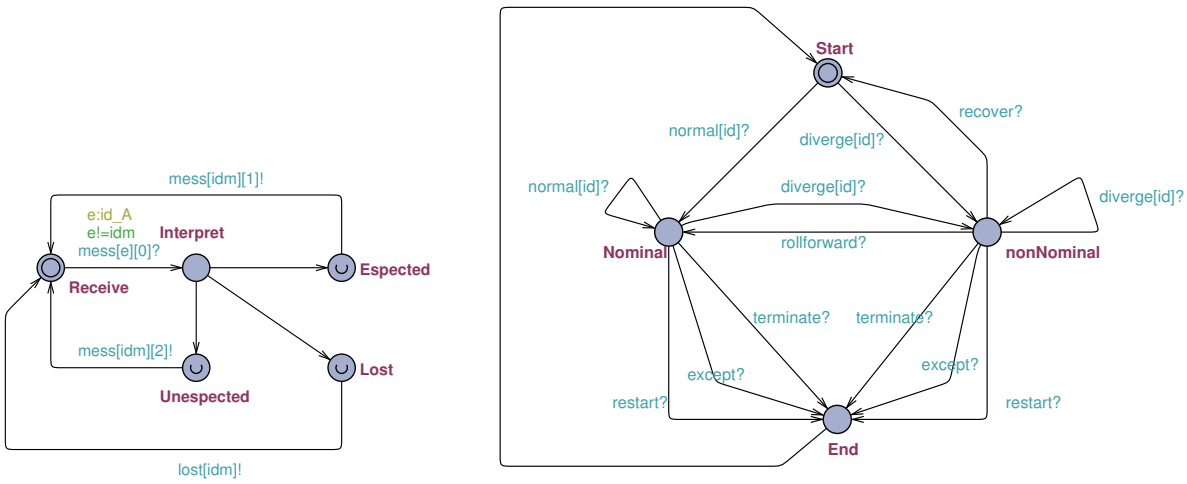

Fig. 7. ActorMessenger (left) and ActorInternalStates Automata (right).

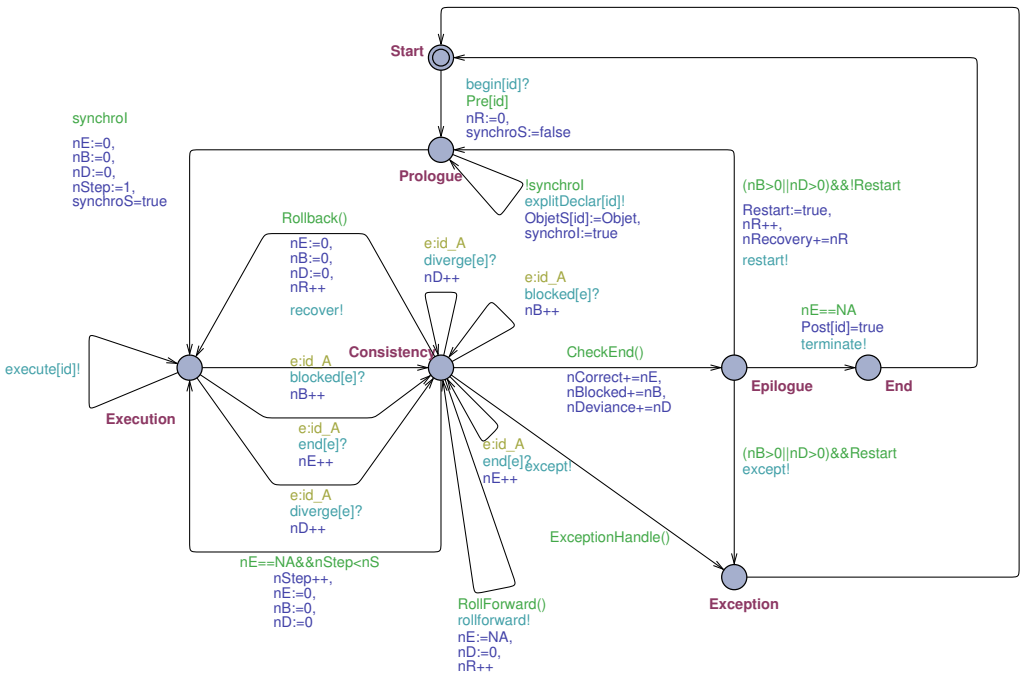

Fig. 8. Situation Model

Reachability. This property can be understood as: is there a path starting at the initial state, such that given state formula is eventually satisfied along that path (Behrmann *et al.*, 2004). We are particularly interested in checking the reachability of all end states: scenario end, situation end and actor's nominal behavior end. These properties do not, by themselves, guarantee the correctness of application execution and actor interactions, but they validate the basic behavior of the model. In Uppaal, we write this property using the syntax $E <> \varphi$

- **E<>Scenario.End**: the application scenario is executed right to the **End** state.
- **E<>Situation(0).End**: the situation S0 can reach the normal end.
- **E<>Situation(1).End**: the situation S1 can reach the normal end.
- **E<>Situation(0).Exception**: the situation S0 can reach the exception treatment exit.
- **E<>Situation(1).Exception**: the situation S1 can reach the exception treatment exit.
- **E<>ActorLogic(0).End and ActorLogic(1).End**: two actors can realize their nominal actions or preserve their interaction consistency.

These verified properties show that consistency

management can preserve system's nominal behaviors by supervising actor's interactions.

Safety. Safety property expresses that under certain conditions, something bad will never happen (Prigent *et al.*, 2005). It guarantees the respect of structural constraints. It is verified in Uppaal by using path formulas $A[]\varphi$ and $E[]\varphi$ where φ is the state formula.

• **A[] not (Situation(0).nE>NA)**: the number of actors in situation S0 that reach **End** location is not higher than the total number of actors *NA*.

• **A[] not (Situation(0).nB>NA)**: the number of actors in situation S0 that are in **Blocked** location is not higher than the total number of actors *NA*.

• **A[] not (Situation(0).nD>NA)**: the number of actors in situation S0 whose actions diverge is not higher than the total number of actors *NA*.

• **A[] not (Situation(0).nE + Situation(0).nB + Situation(0).nD > NA)**: the number of state confirmation messages sent by the actors is not higher than the total number of actors *NA*.

• **A[] not (Situation(0).End and Situation(0).nE < NA)**: situation S0 reaches the normal end with at least all participant actors finished their interaction correctly.

The same properties for situation S1 are also verified. This checking shows the strict control of consistency management on the choice of appropriate mechanisms according to actors' states.

Absence of deadlock. Absence of deadlock or deadlock free system is when the system will never move up to a state where there is no possible progress.

• **A[] not deadlock**: models are deadlock free.

Interactive application execution is an unpredictable process caused by uncontrollable actors' actions. The conceived Uppaal models represent an abstract point of view of system's components logic and consistency management layer control. Moreover, thanks to Uppaal simulator and its query language, we can validate, step by step, system execution and verify several important properties concerning integrated misunderstanding handling. All previous properties are verified. That shows the structural correctness of our proposed approach.

8. Online Distance Learning case study

To validate our approach we applied our situation-based methodology in our current online distance learning (ODL) project (Trillaud *et al.*, 2012). The project is devoted to the development of an online distributed platform that simulates a real classroom: teachers and learners carry out learning sessions as in a real life but by interacting through a virtual class environment[3]. The platform integrates an interactive numeric board, camera, microphone and pedagogic tools (as file sharing system or virtual notebook) to support the courses... Fig. 10 shows an example of courses scenario based on 6 situations. The users may face many difficulties: class supervision, course quality assessment, misunderstandings due to the weak system's interfaces and mechanisms to catch and manage user behaviors. The interactions between the actors in ODL contains numerous factors that may lead to misunderstandings as: multi-meaning or implicit behaviors; supervision tools' observation and interpretation imperfection; system component failures; incomplete, missing, implicit or wrong consigns...

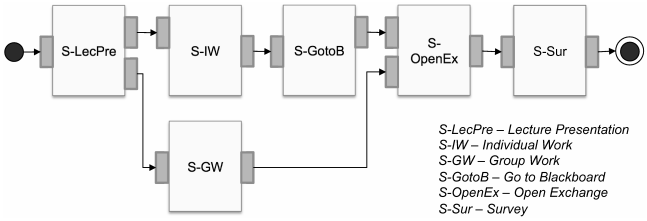

Fig. 10. Situation-based scenario example

8.1. *Individual Work* Situation Description. To deal with these various misunderstandings, we applied our situation-based solution including consistency management to a particular situation: *Individual Work* (SU - IW in Fig. 10). Each learner will work individually and has to do the exercises distributed by the system. The system provides additional exercises each time the learners send the previous exercises report. The expected post-condition is that all the learners reach a required knowledge level *MaxKnowledge*.

Because of the long test duration and development for the real platform prototype, we chose to experiment our misunderstanding management mechanisms and agent-based architecture through a multi-agent simulation with the GAMA platform[4]. All system's actors are modeled and simulated using this platform. We use probabilistic models to represent human actors behaviors. Even though, the simulated agents do not behave exactly as real people does, it is sufficient for our purpose because we aim to illustrate and to check the benefits of our consistency management mechanisms on a simple case study. Moreover, the simulation experimentation allows parameters tuning and comparison of several experimentation campaigns[5].

8.1.1. The agents. We have 4 types of agents: *Teacher*, *Learner*, *Observer* and *ODL System*. The *Observer's* role

[3] `http://foad-l3i.univ-lr.fr/portail/` (in french)

[4] `https://code.google.com/p/gama-platform/`

[5] We started to perform the same experimentation on our ODL environment prototype mentioned above (work in progress).

is to observe the state of sent exercises in order to evaluate learners' accumulated knowledge level. The distribution mechanism based on these observations and learners' skill level evaluations is taken in charge by *ODL System agent* that is a combination of the 3 other agents of our model, introduced in section 5: *Scenario*, *Script* and *Director* agents (Fig. 4).

The *Learner agent* has to connect to the classroom before receiving the distributed exercises. The factors that influence exercise finishing probability are: exercise difficulty level, deadline and learner's smart level. Learner's knowledge level in current session is updated after each sent and corrected exercise, and this level will be used by its own *Observer agent* to determine if he reached the required level and the exercise distribution will end.

The *Observer agent's* role is the go-between between the learner under its responsibility and the ODL system. It observes and estimates learner's state and transfers it to the system. *Observer* has to check the result of exercise rapport: finished or not, accuracy rate, and also supervise learner's knowledge level in order to be able to notify exercise session ending to ODL system.

The *Teacher agent* in this situation plays the role of a moderator by supervising all learners work and checking exercise distribution undertaken by the ODL system.

The *ODL System agent* is a special agent that represents and simulates all the remainder components in our online distance learning platform, including the other system actors, software and pedagogic resources according to our overall architecture in Fig. 4.

8.1.2. Interaction between Agents and Consistency Mechanisms. Fig. 11 summarizes the main interactions representing the communications between the agents above. To start exercise session, the teacher and all of the learners have to connect first. The first exercise will be calculated with a random difficulty level and a random deadline. This first decision will be validated or not by the teacher and then sent to the corresponding learner if accepted. Once the learner receives distributed exercise, he begins working and sends the rapport after finishing. This rapport will be analyzed by the *Observer agent* in charge, before redirecting it with observing data to *ODL System*. The observing data contain exercise finishing state, accuracy rate, learner knowledge level and estimated learner smart level. ODL System uses this observing data for the next distribution: exercises will be adapted to learner's smart level so that he can finish it with higher accuracy rate. This strategy suits naturally to learner's desire to be able to terminate exercise session as soon as possible.

However, the observation is never perfect, The *Observer agent* can commit error implying wrong observing data. Potential misunderstandings in this situation may occur when the system distributes exercises that are incoherent given the learners' skills and expectation. They can result from wrong learners' exercise state observation or from inappropriate distributed exercise level. The misunderstanding handling is done inside the situation during its 3-phase progression.

Prologue phase: The system checks each learner's connection status to begin the exercise series distribution.

Dialogue phase: In this situation, the interactions content refers to the exercises distribution and reporting. During learners' work, each *Observer agent* supervises its associated learner's working state and his exercise report to collect data: partial or total termination, work duration, correctness rate. To avoid the wrong estimation of learner's skill and knowledge level, the *Observer* synchronize some of the observed data by asking the *Learner* to agree with the collected data before to forward the report to the *ODL System*. This synchronization does not intend to correct the observation but just to check wether or not this observation is accurate for the simulation analysis purpose.

Epilogue phase: To finish the situation the learners must reach a given skill level after a given number of exercises. If a learner reaches this number without reaching the required skill level, the series will be stopped after a *session deadline* to avoid an abnormal long series. The system sends a *StopSignal* message to all learners to confirm the end of the exercise series after a predefined timeout. It refers to the exception treatment.

8.2. Experimentation Results. We run the simulation of *Individual Work* situation with the following parameters: 50 learners, 1 teacher, max knowledge level = 25, max difficulty level = 20, session deadline = 250 steps of simulation. We will measure a set of important factors influenced by potential misunderstandings:
N_e: total number of distributed exercises;
N_{notend}: total number of real non-finished exercises;
N_{bad}: number of bad observation by all observers;
N_{cor}: number of system observation corrections while detecting the wrong observed states (it refers to the synchronization times where consistency management is performed to remove incoherent data);
LI: learners' interest level that increases when the learners succeed and that decreases when they fail their exercises;
T_{total}: total session times (in *steps*) until the last learner has finished his series.

The data are recorded and calculated for the average values from 10 simulations launching times in each measure. We compare these data between two cases: "With" and "Without" the consistency management. The results are summarized in Table 1. The total distributed exercises number N_e is twice more in "Without" case

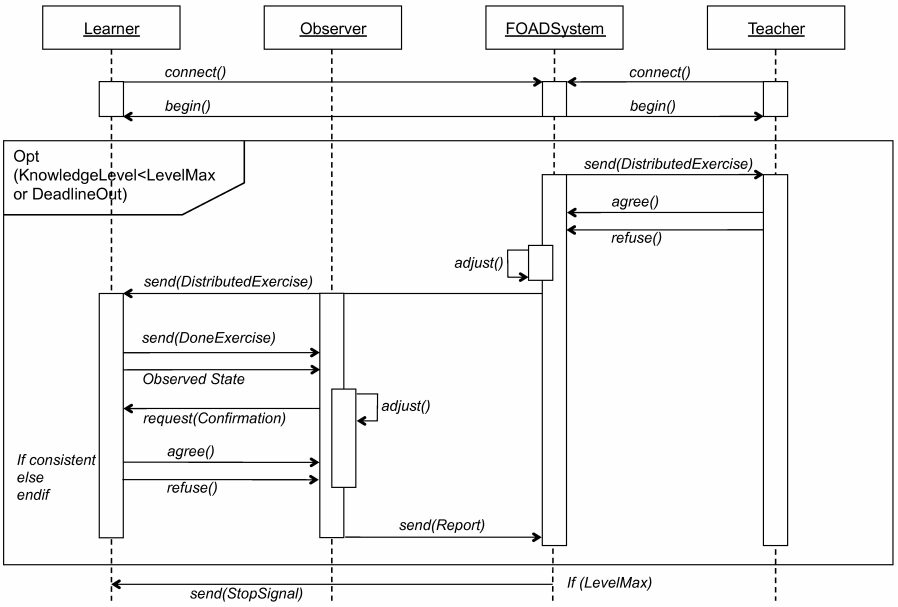

Fig. 11. Agents main interactions in the simulation

Table 1. Statistical data comparison between 2 cases: With (Wi) et Without (Wo) the consistency management

	N_e		N_{notend}		N_{bad}		N_{obsnon}		N_{cor}		LI		T_{total}	
	Wi	Wo	Wi	Wo	Wi	Wo	Wi	Wo	Wi	Wo	Wi	Wo	Wi	Wo
1	330	735	23	64	83	103	93	114	83	0	78.98	66.1	988	2692
2	363	692	45	28	87	76	110	88	87	0	77.73	76.41	1104	2640
3	361	744	44	55	94	97	114	114	94	0	76.35	69.06	1076	2700
4	383	768	47	73	110	99	129	118	110	0	77.31	65.18	1160	2724
5	347	744	32	60	87	99	109	115	87	0	77.94	67.31	1024	2688
6	360	806	37	65	111	117	122	135	111	0	77.55	64.68	1108	2760
7	392	737	66	59	93	92	118	108	93	0	73.06	66.88	1188	2692
8	379	752	42	66	117	100	131	112	117	0	77.65	65.88	1140	2712
9	353	722	37	69	96	100	111	111	96	0	77.49	67.55	1048	2672
10	361	774	40	62	93	115	117	134	93	0	74.18	65.92	1084	2728
Ave.	363.4	747.4	42.4	60.1	97.1	99.8	115.9	114.9	17.8	0	76.82	67.71	1092	2641

compared to the "With" case. The average number of not finished exercises in "Without" series is higher than in "With" series: 747.4 vs 363.4 also depicted in Fig. 12 (left). It is obvious that the session duration in "Without" case is almost 2 times longer than in "With" case.

Fig. 12 (right) shows the number of learners that have finished their whole series during the situation execution in the "With" and "Without" consistency management cases. The lines shows that the learners work with more exercises and with longer duration T_{total} in the "Without" case. We can make the same observation with the average measure values in Table 1.

Why do we have this difference result? When the consistency management is integrated in the situation execution to handle the potential misunderstandings, the observers have to adjust their observed data according to learners' *disagree*' acknowledgements. Hence, the learner's skill level estimation will converge faster to the real value, and the difficulty level of the distributed exercises is more appropriate to his skills. The result is that learners can finish all the exercises and with higher correctness rate. In contrast, if no mechanism is added to control the inconsistency between learners and observers, a non-finished exercise can be perceived as finished, and vice versa. The skill estimation is less correct: higher or lower than the real one. There is a higher probability that the ODL system gives to the learners too difficult or too easy exercises. That delays the skill level progression making the learners take more time to terminate the series.

9. Conclusion

In this paper, we have presented the situation-based design methodology and consistency management mechanisms to handle the misunderstanding in interactions. Our approach is to contextualize the interactions between actors into *situations* and add to these basic narrative blocks consistency management mechanisms split into

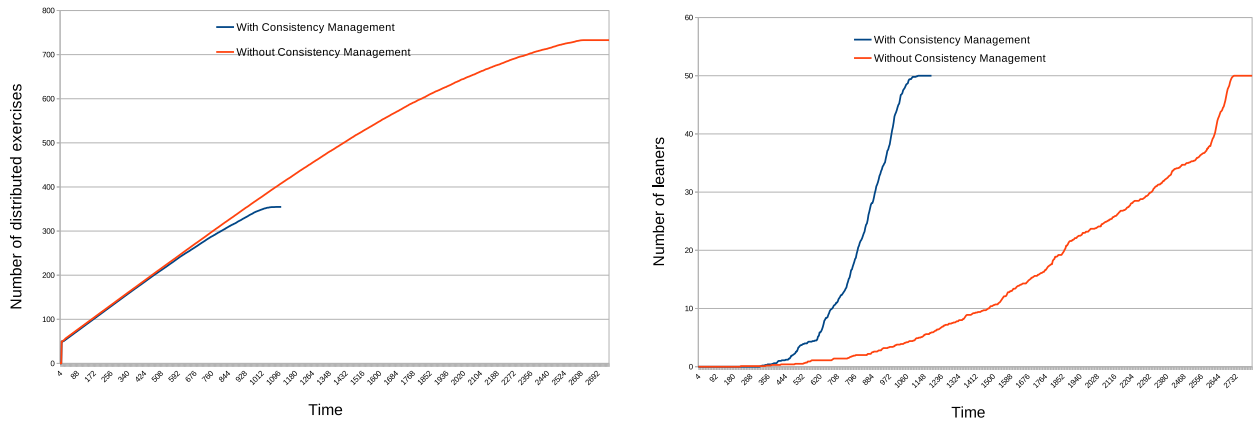

Fig. 12. Comparison between 2 cases "With" and "Without" consistency management.

3 steps: the *Prologue*, data declaration and consistency verification, the *Dialogue*, the interaction unfolding, local visions synchronization and misunderstanding treatment, and the *Epilogue*, data update and agreement attainment. Our aim is to provide a management pattern that could be systematically used by the application designers or developers and that allow them to incorporate their own verification, synchronization, prevention and tolerance mechanisms adapted to the specific misunderstandings of their applications.

We have formally modeled the proposed approach using Uppaal tool in order to validate important structural properties. We have also applied our methodology to a case study from an Online Distant Learning project. We built a simulation of the *Individual Work* situation and integrated into it the proposed solutions to show how the consistency management operates on a simulation example. From the experimentation results, we have found out that our mechanisms reduce the incoherent data between learners and observers and improve the performance of exercise distribution: shorter session duration, lower exercise number, faster required level attainment... Even if the simulation is simple and does not cover exhaustively all the possible interactions that can occur in such situation, it illustrates the benefits of misunderstanding management during interaction progression.

The presented work focuses on the architectural and structural part of our approach. Our current research in progress aims to complete this work from the algorithmic point of view. Were are developing the post/pre condition matching algorithms and multiple criteria based decision algorithms for situation selection. The first results are presented in the work of (Ho *et al.*, 2014).

References

Barber, H. and Kudenko, D. (2008). Generation of dilemma-based interactive narratives with a changeable story goal, Int. Conf. on INtelligent TEchnologies for Interactive enterTAINment, Cancun, Mexico, pp. 6:1–6:10.

Behrmann, G., David, A. and Larsen, K. (2004). A tutorial on uppaal, in M. Bernardo and F. Corradini (Eds), Formal Methods for the Design of Real-Time Systems, Vol. 3185 of LNCS, Springer Berlin Heidelberg, pp. 200–236.

Champagnat, R., Delmas, G. and Augeraud, M. (2010). A storytelling model for educational games : Heros interactive journey, Int. Journal of Technology Enhanced Learning **2**(1): 4–20.

Combefis, S. and Pecheur, C. (2009). A bisimulation-based approach to the analysis of human-computer interaction, ACM SIGCHI Symp. on Engineering Interactive Computing Systems (EICS'09), Pittsburg, USA, pp. 101–110.

Dang, K. D., Pham, P. T., Champagnat, R. and Rabah, M. (2013). Linear logic validation and hierarchical modeling for interactive storytelling control, in D. Reidsma, H. Katayose and A. Nijholt (Eds), Int. Conf. on Advances in Computer Entertainment Technology (ACE 2013), Vol. 8253 of LNCS, Springer International Publishing, Enschede, Netherlands, pp. 524–527.

Dey, A. K. (2001). Understanding and using context, Personal and Ubiquitous Computing **5**(1): 4–7.

Dourish, P. (2004). What we talk about when we talk about context, Personal and Ubiquitous Computing **8**(1): 19–30.

Ho, H. N., Rabah, M., Nowakowski, S. and Estrailler, P. (2014). Trace-based weighting approach for multiple criteria decision making, Journal of Software **9**(8): 2180–2187.

Hommel, B., Pösse, B. and Waszak, F. (2000). Contextualization in perception and action, Psychologica Belgica **40**(4): 227–245.

Jiang, H. (2005). Confidence measures for speech recognition: A survey, Speech Communication **45**(5): 455–470.

Karlsson, B., Ciarlini, A. E. M., Feijo, B. and Furtado, A. L. (2006). Applying a plan-recognition / plan-generation paradigm to interactive storytelling, Workshop on AI Planning for Computer Games and Synthetic Characters (ICAPS'2006), Cumbria, UK, pp. 31–40.

Karsenty, L. and Botherel, V. (2005). Transparency strategies to help users handle system errors, Speech Communication **45**(3): 305–324.

King, G. G. (2011). General aviation training for automation surprise, Journal of Professional Aviation Training & Testing Research **5**(1): 46–51.

Laprie, J. C., Randell, B., Landwehr, C. and Member, S. (2004). Basic concepts and taxonomy of dependable and secure computing, IEEE Transactions on Dependable and Secure Computing **1**(1): 11–33.

Lebowitz, J. and Klug, C. (2011). Interactive Storytelling for Video Games: A Player-Centered Approach for Creating Memorable Character and Stories, Focal Press.

Lopez-Cozar, R., Callejas, Z. and Griol, D. (2010). Using knowledge of misunderstandings to increase the robustness of spoken dialogue systems, Knowledge-Based Systems **23**(5): 471 – 485.

Magerko, B. and Laird, J. E. (2004). Mediating the tension between plot and interaction, AAAI Workshop Series: Challenges in Game Artificial Intelligence, San Jose, USA, pp. 108–112.

Paul, R., Charles, D., McNeill, M. and McSherry, D. (2011). Adaptive storytelling and story repair in a dynamic environment, in M. Si, D. Thue, E. Andr, J. Lester, J. Tanenbaum and V. Zammitto (Eds), Int. Conf. on Interactive Digital Storytelling (ICIDS), Vol. 7069 of LNCS, Springer Berlin Heidelberg, pp. 128–139.

Pham, P. T., Rabah, M. and Estraillier, P. (2011). Handling the misunderstanding in interactions: Definition and solution, Int. Conf. on Software Engineering & Applications (SEA 2011), Singapore, pp. 47–52.

Pham, P. T., Rabah, M. and Estraillier, P. (2013). Agent-based architecture and situation-based scenario for consistency management, Federated Conf. on Computer Science and Information Systems (FedCSIS 2013), Krakow, Poland, pp. 1041–1046.

Picard, F. and Estraillier, P. (2010). Context-dependent player's movement interpretation application to adaptive game development, Three-Dimensional Image Processing (3DIP) and Applications, Vol. 7526 of Proc. SPIE, San Jose, USA, pp. 75260W–75260W–9.

Prigent, A., Champagnat, R. and Estraillier, P. (2005). Scenario building based on formal methods and adaptative execution, Int. Simulation and Gaming Association Conference (ISAGA2005), Atlanta, USA, pp. 1–19.

Rapaport, W. J. (2003). What did you mean by that? misunderstanding, negotiation, and syntactic semantics, Minds and Machines **13**(3): 397–427.

Sehaba, K., Estraillier, P. and Lambert, D. (2005). Interactive educational games for autistic children with agent-based system, in F. Kishino, Y. Kitamura, H. Kato and N. Nagata (Eds), Int. Conf. on Entertainment Computing (ICEC'05), Vol. 3711 of Lecture Notes in Computer Science, Springer Berlin Heidelberg, Sanda, Japan, pp. 422–432.

Silva, A., Raimundo, G. and Paiva, A. (2003). Tell me that bit again... bringing interactivity to a virtual storyteller, in O. Balet, G. Subsol and P. Torguet (Eds), Virtual Storytelling. Using Virtual RealityTechnologies for Storytelling, Vol. 2897 of Lecture Notes in Computer Science, Springer Berlin Heidelberg, pp. 146–154.

Tanenbaum, A. S. and Woodhull, A. S. (2006). Operating Systems Design and Implementation, Pearson Education.

Trillaud, F., Pham, P. T., Rabah, M., Estraillier, P. and Malki, J. (2012). Situation-based scenarios for e-learning, Int. Conf. on e-Learning (EL 2012), Lisbon, Portugal, pp. 121–128.

Young, R. M., Riedl, M. O., Branly, M. and Jhala, A. (2004). An architecture for integrating plan-based behavior generation with interactive game environments, Journal of Game Development **1**(1): 51–70.

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