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Modeling of Errors Realized by a Human Learner in Virtual Environment for Training

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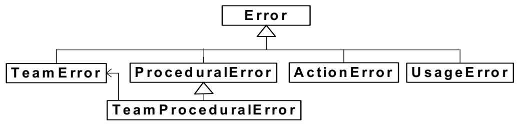
Abstract: This study focuses on the notion of erroneous actions realized by human learners in Virtual Environments for Training. Our principal objective is to develop an Intelligent Tutoring System (ITS) suggesting pedagogical assistances to the human teacher. For that, the ITS must obviously detect and classify erroneous actions produced by learners during the realization of procedural and collaborative work. Further, in order to better support human teacher and facilitate his comprehension, it is necessary to show the teacher why learner made an error. Addressing this issue, we firstly modeling the Cognitive Reliability and Error Analysis Method (CREAM). Then, we integrate the retrospective analysis mechanism of CREAM into our existing ITS, thus enable the system to indicate the path of probable cause-effect explaining reasons why errors have occurred.
Keywords: Intelligent tutoring system, Erroneous actions, Retrospective analysis

1 Introduction

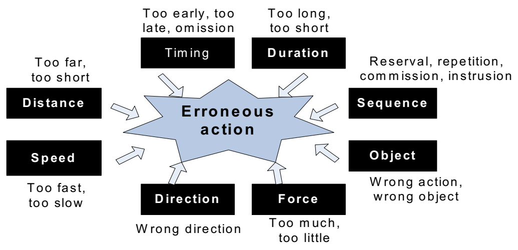
In order to simulate procedural and collaborative work, we developed the model MASCARET (Multi-Agent System for Collaborative Adaptive and Realistic Environment for Training) where human learners and agents collaborate to realize a task [1]. Learners are gathered in team consisting of several predefined roles, every role contains a number of actions to be realized by learners with specific resources. During realization of the tasks, it is essential to take into account that human learners may make erroneous actions in comparing to their predefined correct procedure.

In [2], we have proposed a model of Intelligent Tutoring System (ITS) whose principal objective is to suggest pedagogical assistances to the teacher adapted to the simulation context and to the learner's behaviours (including erroneous actions). However, this works exclusively concerns errors detection and tagging. Once erroneous actions are detected in our existing ITS, it were be classified in different types (cf. Figure 1(a)) whose explications are based on a knowledge base on classical errors. In order to better support the teacher and facilitate his comprehension, it lacks a model that could explain reasons why the learner made an error.

Our approach bases on the Cognitive Reliability and Error Analysis Method (CREAM) in Human



(a) Errors types in ITS [2]



(b) Dimensions of error modes [3]

Figure 1: Errors types and errors's phenotypes

Reliability Analysis field [3]. This approach proposed a classification scheme which makes a distinction between observations of errors (*phenotypes*, cf. Figure 1(b)) and its causes (*genotypes*) classified in three categories: M(an), T(echnology) and O(rganization). For example, since the learner made a mistake about the order of actions, the erroneous action observed is in phenotype *Sequence* and that can be futher explained by some genotypes such as *Inattention* (Man related genotype), *Communication failure* (Technology related genotype), etc. The causal links between phenotype-genotype are represented using a number of consequent-antecedent links. Finally, the scheme could be associated with both a method of retrospective analysis (the search for causes) and a performance prediction method. However, in our goal of erroneous actions detection and then searching for the causes, we interested in human learner's performance analyses, in other words, in retrospective analyses.

Implementation of CREAM was object in the work of El-Kechaï [4][5] which firstly proposed a task model named METISSE in order to recognize learner's plans in Virtual Environments for Training (VET), then this model could be used to detect for erroneous actions according to classification of Hollnagel. Nevertheless, implementation of METISSE was not complete, and integration of CREAM into a really ITS was not performed.

In this paper, we will firstly propose an approach to model CREAM (Section 2). Next, in Section 3, we will present the integration of retrospective analysis mechanism of CREAM into our existing ITS as well as our evaluation.

2 Implementation of CREAM

2.1 Classification Scheme Representation

There are several graphic tools that permit to keep track of analyses processes such as CREAM Navigator developed by Serwy and Rantanen [7]. However, this navigator is completely closed in the sense that it does not maintain an explicit representation of possible errors modes and probable causes. For that, [4] proposed using a rules base for represent consequent-antecedent links, hence the search for the causes was executed by backward inferences. Limitation of this method obviously lies on the performance of inference mechanism, other problem maybe occurs in adding, removing another potential errors that will demand a considerable modification on the rules base. For our development, as suggested in [3], we intent to separate the analysis method (cf. Section 2.3 and 2.4) and the representation of errors modes using a group of four data files in format XML detailed below:

Questionnaire.xml : proposing to represent a list of questions from which we could evaluate the Common Performance Conditions (see Section 2.2 in following).

Phenotype.xml : proposing to maintain the phenotypes and its antecedents (cf. Figure 2).

```
<Phenotypes>
   <Phenotype name="Time/During" description="...">
      <GeneralAntecedents>
         <item>Inadequate plan</item>
         <item>Inattention</item>
      </GeneralAntecedents>
      <SpecificAntecedents>
         <item>Earlier omission</item>
      </SpecificAntecedents>
   </Phenotype>
   ...
</Phenotypes>
```

Figure 2: Representation of phenotypes

Genotype.xml : containing all possible causes classified in three groups (M,T,O), each group is then detailed into several categories. The important point is that this data file also represents relations between each consequent and its antecedents (cf. Figure 3).

Repartition.xml : proposing to determine repartition of specific antecedents (cf. Figure 4) in three factors (M,T,O) which serves to initialize the mass of each specific antecedent as a probable cause (cf. Section 2.4).

Finally, in considering that CREAM is naturally a flexible method and adaptable to different analysis contexts, this strategy of classification scheme representation permits customize the scheme without any modification on analysis method.

```
<Genotypes>
   <Group name="Man">
      <Category name="planning">
         <GeneralConsequent name="Inadequate plan" description="...">
            <GeneralAntecedents>
               <item>Distraction</item>
               <item>Excessive demand</item>
            </GeneralAntecedents>
            <SpecificAntecedents>
               <item>Error in goal</item>
               <item>Inadequate training</item>
            </SpecificAntecedents>
         </GeneralConsequent>
         ...
      </Category>
      ...
   </Group>
   ...
</Genotypes>
```

Figure 3: Representation of genotypes

```
<Repartition>
   <item name="Earlier omission" group="Man" description="..."/>
   <item name="Message misunderstood" group=Technology description="..."/>
   ...
</Repartition>
```

Figure 4: Repartition of specific antecedents in three factors (M,T,O)

2.2 Define the Common Performance Conditions (CPC's)

In CREAM, Hollnagel highlighted that the context strongly influence human actions. It is therefore essential to take into account the description of virtual environment in which the human learner is immersed. The objective is to determine how each factor (M,T,O) influences the training context. Here, we are inspired from the proposition presented in [5] using a predefined questionnaire which will be answered by the teacher before training session (cf. Figure 5). Next, each factor will be assigned one

```
<Questionnaire>
<Question name="The visual quality of the interface is it bad?" group="Technology" answer="Yes"/>
<Question name="Does the learner have concentration trouble?" group="Man" answer="No"/>
...
</Questionnaire>
```

Figure 5: Define the CPC's by questionnaire [5]

coefficient calculated using formula below:

$$Coefficient_{group\,i} = \frac{Number\,of\,Yes\,answers\,associated\,to\,group\,i}{Total\,number\,of\,Yes\,answers} \tag{1}$$

where *group i* is respectively in (Man, Technology, Organization). These values permit define the most probable factor leading to erroneous actions.

2.3 Modelling of Consequent-Antecedent Relations

One advantage of CREAM lies on its recursive analysis approach, rather than strictly sequential in compare with other traditional analysis methods. So that, it also conducts to a non-hierarchical data structure to connect the direct as well as indirect links: *(i)* between a phenotype and its antecedent; and *(ii)* between a consequent and its antecedents. Figure 6 shows our model to represent the connection between consequent-antecedent.

Here, we are going to construct a causal graph where we use the term *node* to point to either a consequent or an antecedent. Each node is described by its *name*; the group of errors modes that it is associated and its *category* in group; the *description* in text helps better explain the error's semantics in particular context. The boolean attribute *terminal* permit to identify if that is a terminal-cause or not. The most important is that, each node contains two lists: one includes its antecedents, other points to its consequents, in others words, they represent edges in/out one node in the causal graph. At last, each node must also

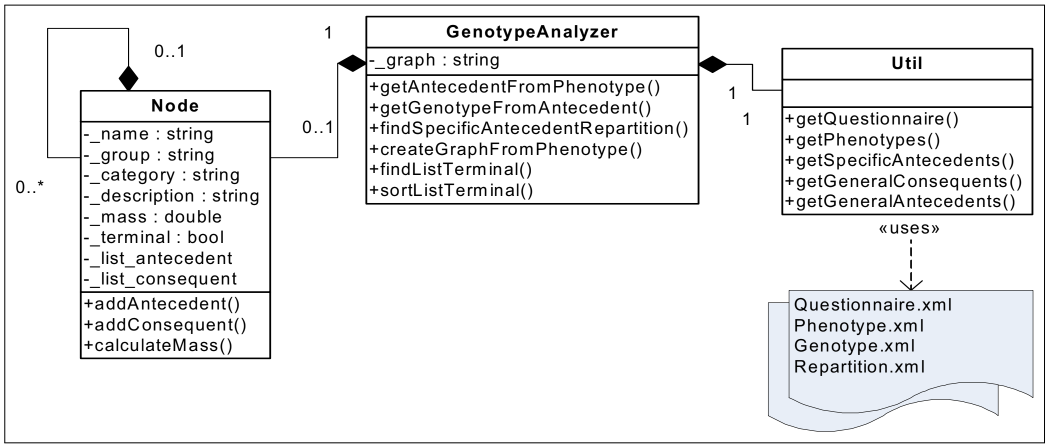


Figure 6: UML diagram for modeling consequent-antecedent links

include a value of *mass* which represent the certitude of choosing this node as a probable cause. The two methods *addAntecedent()* and *addConsequent()* serve for maintaining the two lists of antecedents and consequents of one node. Note that once a node calls the method *addAntecedent()* serving for adding a "parent" node like one of its antecedents, this node will also add itself to the consequents list of the "parent" node (using the method *addConsequent()* of the parent node), the value of the attribute *terminal* then will be set to false.

2.4 Search for the Causes

The retrospective analysis is executed by a *GenotypeAnalyzer* containing *graph* attribute which is initialized by pointing to the phenotype input (root node), then the analyzer calls accurate methods to find the root causes (the nodes with the attribute terminal having value false). This mechanism is presented below (cf. Algorithm 1).

Algorithm 1 Retrospective analysis

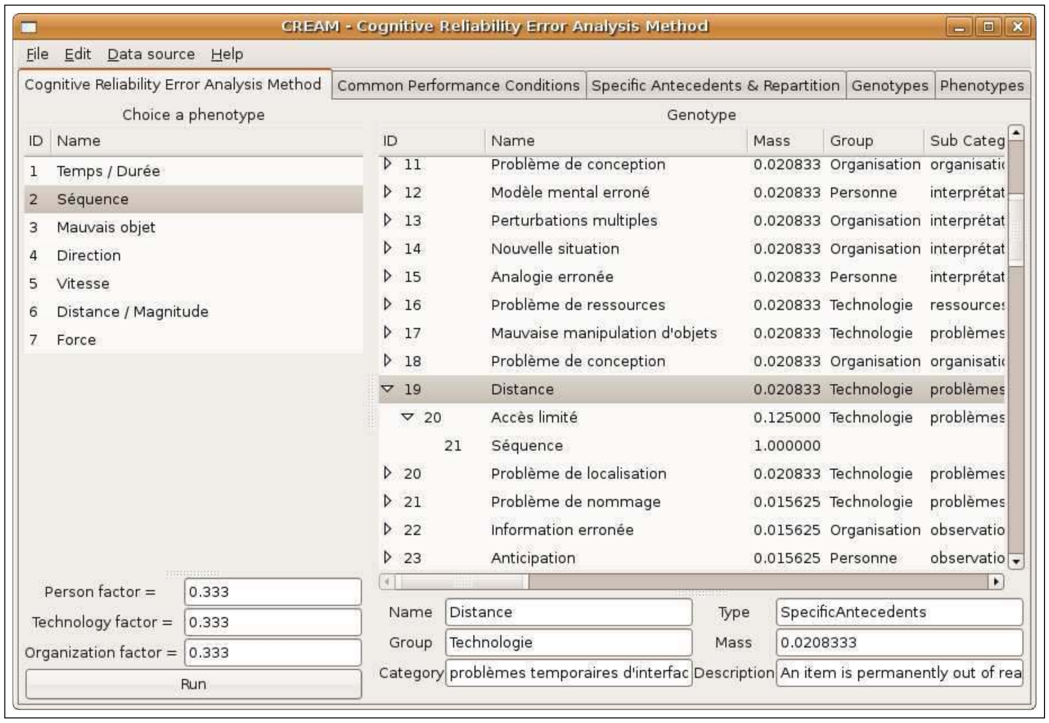
```
Require: Phenotype of erroneous action
 1: Initialization: Construct the "root" node pointing to phenotype input
 2: {Step 1: Finding antecedents of phenotype input}
 3: Read from file Phenotype.xml, find all general antecedents of phenotype input
 4: for each antecedent do
 5:     Add it into antecedents list of "root" node
 6: end for
 7: {Step 2: Construction the causal graph}
 8: for each unvisited node in the graph do
 9:     Find its antecedents from file Genotype.xml
10:     Add them to antecedents list
11: end for
12: Return Step 2. This recursive search terminates when the node selected is a specific antecedent node
    or a general consequent node without antecedents.
```

With this algorithm, we finally attain a causal network where each node is associated with its antecedents and consequents. The "leaves" are terminal nodes (or "root" causes) whose antecedents list is empty. In order to calculate the certitude of choosing each node as a probable cause, we inherit the proposition presented in [5] using Dempster-Shafer's evidence theory:

$$mass(a) = coefficient\,(g\,(a)) * \sum_{\forall c \in Cons(a)} \left(\frac{mass(c)}{\sum_{\forall i \in \{M,T,O\}} (coefficient(i) * n_{ic})} \right) \tag{2}$$

where:

- $mass(a)$: mass of antecedent a
- $g(a)$: group of a
- $Cons(a)$: consequents list of a
- $coefficient(i)$: coefficient of group i calculated in Formula 1
- n_{ic} : number of antecedents of c classified in group i


CREAM - Cognitive Reliability Error Analysis Method
File Edit Data source Help
Cognitive Reliability Error Analysis Method
Common Performance Conditions
Specific Antecedents & Repartition
Genotypes
Phenotypes
Run

Choice a phenotype

ID	Name
1	Temps / Durée
2	Séquence
3	Mauvais objet
4	Direction
5	Vitesse
6	Distance / Magnitude
7	Force

Person factor = 0.333
Technology factor = 0.333
Organization factor = 0.333

Genotype

ID	Name	Mass	Group	Sub Categ
11	Problème de conception	0.020833	Organisation	organisati
12	Modèle mental erroné	0.020833	Personne	interprétat
13	Perturbations multiples	0.020833	Organisation	interprétat
14	Nouvelle situation	0.020833	Organisation	interprétat
15	Analogie erronée	0.020833	Personne	interprétat
16	Problème de ressources	0.020833	Technologie	ressource
17	Mauvaise manipulation d'objets	0.020833	Technologie	problèmes
18	Problème de conception	0.020833	Organisation	organisati
19	Distance	0.020833	Technologie	problèmes
20	Accès limité	0.125000	Technologie	problèmes
21	Séquence	1.000000		
20	Problème de localisation	0.020833	Technologie	problèmes
21	Problème de nommage	0.015625	Technologie	problèmes
22	Information erronée	0.015625	Organisation	observatio
23	Anticipation	0.015625	Personne	observatio

Name: Distance
Type: SpecificAntecedents
Group: Technologie
Mass: 0.0208333
Category: problèmes temporaires d'interfac
Description: An item is permanently out of rea

Figure 7: CREAM Explorer

Finally, the Figure 7 illustrates our tool - CREAM Explorer which was developped in this phase permitting to maintain the errors scheme, answer the questionnaire for define the CPC's and execute the retrospective analysis.

3 Integration of Retrospective Analysis into our existing ITS

3.1 Learner's Plans Recognition

In order to detect the erroneous actions realized by a human learner, it is indispensable to know:

(i) the learner's activities in the past;

(ii) his current action (in the meaning that the action has just been done);

(iii) the actions that the human learner intents to do in according to a predefined correct procedure.

Our existing ITS as proposed in [2] bases on the model MASCARET [1] where we used an multi-agent system to simulate collaboration between human learners and agents during their realization of tasks. Learners are gathered in team consisting of several predefined roles, every role contains a number of tasks associated eventually with accurate resources, every leaner also owns an epistemic memory containing all actions realized in the past, etc. Finally, we could retrieve from MASCARET following informations relating to learner's plan in VET:

- *action(s) before*: learner's action(s) in the past (note that, in MASCARET, every action is eventually associated with its accurate resource(s))
- *current action*: action has just been done by learner
- *action(s) correct (according to role)*: action(s) must be done by learner in his role(s)
- *action(s) correct (according to plan)*: action(s) may be done by learners in the context. Here, it is essential to make distinction betweens *action(s) correct according to role* and *action(s) correct according to plan*. In the first case, because the learner could play several roles, it represents all correct actions that the system expects from the learners. The second one concerns the cases where there are more than one learner in VET to realize together a mission. Therefore, in this case, it is possible that a leaner performs a correct action according to the plan but it is not correct in compare to his role.
- *next correct action(s) in the role*: next action(s) must be done by learner in his role(s)
- *full correct plan*: description of all accurate actions (associated with resources) in predetermined procedure that the learner must respect.

In next section, we present our mechanism for mapping erroneous actions detected by our existing ITS with Hollnagel's classification scheme of errors modes.

3.2 Classification of Erroneous Actions according to the Scheme of CREAM

Erroneous Actions in Phenotype "Sequence"
According to Hollnagel, performing an action at the wrong place in a sequence or procedure is a common erroneous action, and it is more realistic in our context of simulation of procedural and collaborative work. The *"Sequence"* problem consists of several specific effects: *Omission* (an action was not carried out); *Jump forward/ Jump backwards* (actions in a sequence were skipped/carried out again); *Repetition* (the previous action is repeated); *Reversal* (the order of two neighbouring action is reversed); *Wrong action* (an extraneous or irrelevant action is carried out). We present in following our mechanism to detect erroneous actions in phenotype *"Sequence"*:

Algorithm 2 Detection of erroneous actions in phenotype *Sequence*

```
1:  if current action exists in actions correct according to role then
2:      this is a correct action (phenotype Sequence does not occur)
3:  else
4:      if current action does not exist in actions correct according to plan then
5:          specific effect = "Wrong action"
6:      else
7:          if current action exist in last action before then
8:              specific effect = "Repetition"
9:          end if
10:         Compare the relative order of current action to the order of next correct action(s) in the role
            using the full correct plan
11:         if id current action < id correct action in role then
12:             specific effect = "Jump backwards and/or Omission"
13:         else
14:             specific effect = "Jump forward and/or Omission"
15:         end if
16:         if id current action = id correct action in role + 1 then
17:             specific effect = "Reversal"
18:         end if
19:     end if
20: end if
```

Erroneous Actions in Phenotype "Wrong object"
In [3], the author clarified that *"action at wrong object"* is one of the more frequent error modes, such as pressing the wrong button, looking at the wrong indicator, etc. In our context, during realisation of

collaborative work, it is possible that learner performs a correct action but on a wrong object. Therefore, the detection of erroneous actions in phenotype *"Wrong object"* must be implemented independently with the detection of phenotype *"Sequence"*. This phenotype is detailed into following specific effects: *Neighbour/Similar object* (an object that is proximity/similar to the object that should have been used); *Unrelated object* (an object that was used by mistake).

In order to detect erroneous actions in phenotype *"Wrong object"*, we use the same principle presented in the case of phenotype *"Sequence"* by using following informations retrieved from model MASCARET:

- *current resource*: resource associated with *current action*
- *resource(s) correct (according to role)*: resource(s) must be used by learner in his role(s)
- *resource(s) correct (according to plan)*: list of resource(s) associated with all action(s) in *action(s) correct according to plan*.

Our algorithm is detailed in following:

Algorithm 3 Detection of erroneous actions in phenotype *Wrong object*

```
1: if current resource exists in resource(s) correct according to role then
2:     this is a correct resource (phenotype Wrong object does not occur)
3: else
4:     if current resource does not exist in resources correct according to plan then
5:         specific effect = "Unrelated object"
6:     else
7:         specific effect = "Neighbour and/or Similar object"
8:     end if
9: end if
```

Erroneous Actions in Phenotype "Time/During"
The phenotype *Time/During* is divided in several specific effects: *Too early/ Too late* (an action started too early/too late); *Omission* (an action that was not done at all); *Too long/Too short* (an action that continued/was stopped beyond the point when it should have been). Hollnagel noted that the error modes of timing and duration refer to a single action, rather than to the temporal relation between two or more actions. In our context, the realization of tasks in model MASCARET is sequential, therefore, an action is considered to be too early when it was realized before several actions in plan; also, action(s) are considered to be omitted when they were not carried out.

Finally, in order to detect erroneous actions in phenotype *Time/Durring*, we propose that:

- action having specific effect *Jump forward* also has specific effect *Too early*
- action described by specific effect *Omission* (in error mode *Sequence*) will be considered as an action having specific effect *Omission* (in error mode *Time/During*)

3.3 Experiment & Results

In order to evaluate our integration of retrospective analysis into ITS, we take place in GASPAR application [6] whose objective aims at simulate aviation activities by virtual reality. The learners are immersed in virtual environment simulating the aircraft carrier in order to realize together the tasks. During the realization of these collaborative works, our ITS follows the learners and then apply the algorithms depicted above for detecting learner's erroneous actions. Next, for interpreting the causes of errors, we use the classification scheme of error modes proposed in [5] which were particularly adapted to VET. Table 1 and Table 2 respectively illustrate results of retrospective analysis for the phenotype Sequence and Wrong object.

We change coefficients of three factors (M,T,O) for evaluating how CPC's influence the analysis result. For each phase in analysis process, we select and display the most probable cause by ordering mass values.

Coefficient (M,T,O)	**Causal links**
(0.333 - 0.333 - 0.333)	1, Design failure (0.125) → Inadequate scenario (0.125) → Sequence
	2, Adverse ambient condition (0.125) → Inattention (0.125) → Sequence
	3, Long time since learning (0.042) → Memory failure (0.125) → Sequence
(1 - 0 - 0)	1, Other priority (0.2) → Memory failure (0.2) → Sequence
	2, Error in mental model (0.067) → Faulty diagnosis (0.2) →Sequence
	3, Erroneous analogy (0.067) → Faulty diagnosis (0.2) → Sequence
(0 - 1 - 0)	1, Equipment failure (0.1) → Access problems (0.5) → Sequence
	2, Distance (0.1) → Access problems (0.5) → Sequence
	3, Localisation problem (0.1) → Access problems (0.5) → Sequence
(0 - 0 - 1)	1, Noise (1) → Communication failure (1) → Sequence

Table 1: Causal links of phenotype *Sequence*

Coefficient (M,T,O)	**Causal links**
(0.333 - 0.333 - 0.333)	1, Access problems (0.125) → Wrong object
	2, Design failure (0.125) → Inadequate scenario (0.125) → Wrong object
	3, Adverse ambient condition (0.042) → Inattention (0.125) → Wrong object
(1 - 0 - 0)	1, Fatigue (0.1) → Performance variability (0.2) → Wrong object
	2, Virtual reality sickness (0.1) → Performance variability (0.2) → Wrong object
	3, Anticipation (0.05) → Wrong identification (0.2) → Wrong object
(0 - 1 - 0)	1, Access problems (0.5) → Wrong object
(0 - 0 - 1)	1, Noise (1) → Communication failure (1) → Wrong object

Table 2: Causal links of phenotype *Wrong object*

4 Conclusion & Future Work

In this paper, we proposed an approach to modelling the Cognitive Reliability and Error Analysis Method (CREAM). We separated the representation of classification scheme of erroneous actions and the analysis method; therefore, our description of errors modes is adaptable to different training context without any modification on analysis method. We started by defining the Common Performance Conditions, then the direct and indirect relations between consequent-antecedent are modelled using a non-hierarchical data structure. Finally, the most probable cause-effect links could be found using Dempster-Shafer's theory presented in [5].

In order to integrate the retrospective analysis described above into our existing ITS, we based on the model MASCARET to retrieve information concerning learner's plans and then detect erroneous actions. Finally, we presented our proposition to mapping erroneous actions with Hollnage's classification. The experimental results in GASPAR project are also presented. So that, in addition to the detection and tagging of erroneous actions, the ITS could furthermore indicate the path of probable cause-effect explaining reasons that the errors occur.

In the future work, we will concentrate our attention on evaluation of MASCARET so that this model could permit to describe more complex tasks in taking into account other factors such as force, distance, speed, direction, etc. Hence, other different types of errors modes could be detected and then explained using the retrospective analysis.

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