Target the controls during the problem solving activity, a process to produce adapted epistemic feedbacks in ill-defined domains.

The case of a TEL system for orthopaedic surgery

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ABSTRACT

In this paper we study one feedback process which is adapted to ill-defined domains. Indeed, this process use others aspects than expected solutions to propose a feedback. The feedback process is based in a set of didactical aspects. In particular, the feedback targets the control element of knowledge, i.e. the knowledge that allows to validate one step in the problem solving process. The paper describes the feedback process and its implementation in the framework of one TEL system in orthopedic surgery.

Keywords

Control knowledge, feedback process, ill defined domain, and didactical decision.

1. INTRODUCTION

In ill defined domain one of the challenges is to continue to develop new tutoring strategies and seek out ways to combine existing strategies [13]. This challenge still open in particular when the domain has multiple and controversial solutions or ill-defined task structures [4]. In this framework our research question is how to design a tutoring feedback system which is not only based in defined solutions but in the known characteristics of knowledge and learning situations.

We study one kind of feedback which is adapted and epistemic. It is adapted because it takes into account the individual differences in relation to incoming knowledge and skills among students [18]. It is epistemic because it is specific to the piece of knowledge at stake and its learning characteristics. Compute an epistemic feedback involves knowledge from the learner, the learning situation and the learning domain [11].

We design a process to produce adapted epistemic feedbacks which includes one decisional model based in a set of didactical hypothesis. The process was implemented and tested in the case of orthopedic surgery.

The research discussed in this paper is developed in the framework of the TELEOS[1] platform [9] which is a Technological Enhanced Learning environment for orthopaedic surgery. This platform proposes a set of resources for the student (haptic simulator, online course, clinical case database) and a diagnosis system able to analyse the student productions and make a knowledge diagnosis based in identified controls.

Based in the model presented in this paper we add a feedback system in the TELEOS environment. This implementation proposes a formative feedback which is delayed, i.e. at the end of the exercise in the simulator. The model is presented in the section 4 and the TELEOS example is presented in the section 5.

2. RELATED WORKS

In some domains (like percutaneous screw fixations in orthopaedic surgery) the *knowledge* obtained by experience plays an important role for both the expert teacher and the novice learner during a problem-solving process. This kind of knowledge, often tacit, refers to "work-related, practical know-how that typically is acquired informally as a result of on-the-job experience, as opposed to formal instruction." [22]. This kind of knowledge is pragmatic, obtained by experience. Moreover a skillful learner, even a domain expert, often makes several attempts before arriving at an acceptable solution: the person makes an error and then tries to correct the error several times. Also there are multiple solutions and because some parts of the knowledge are tacit the strategic to a good solution are unclear. This kind of problem is ill structured. Indeed, an ill-structured problem as one that is complex, with indefinite starting points, multiple and arguable solutions, or unclear strategies for finding solutions [19].

Several works address the problem to model ill defined knowledge and build feedback from these models ([13] and [20]). Based in this previous works, Fournier-Vigier et al. [5] pointed the design feedback difficulties in ill defined domains, in particular the difficulties to provide domain knowledge in ill structure problems. All studied paradigms (cognitive task analysis, constraint-based modeling, expert system, data mining algorithms) propose to describe task models using different techniques. The task models could be complete or partial. In all cases the model is used to offer assistance to the learner (ibid. 234). Most of the feedback systems in these approaches try to guide the student to the intended solution, even if it is described partially and beside most of the feedback are goal oriented.

We aim to study a model of feedback that is not only based in calculated solutions. We explore another feedback paradigm which is centered in the validation process more than the attended solution. In others words the feedback will be related to the characteristics of the controls brought into play during the problem solving process: it was brought into play in the right moment? It was valid or invalid? What is its nature ?

We would like to investigate how to produce an adapted epistemic feedback that takes into account these knowledge characteristics and is able to handle the uncertainty coming from

[1] http://teleos .imag.fr

the diagnosis results. Indeed, like more and more intelligent tutoring systems, we chose to use Bayesian network for our diagnostic knowledge.

From adaptive point of view, Shute & Zapata-Rivera [18] propose a four-process adaptive cycle connecting the learner to appropriate educational materials and resources. This four process cycle include (ibid. p 9) *capture* of the information about the learner, *analyze* the information in relation to the learner model, *select* the information for a particular learner and *present* specific content to the student.

In relation to the selection step of the feedback, few systems propose a computer model which describes the decision of a pedagogical feedback following an uncertain diagnosis. Mayo and Metrovic [14] introduce the idea of Pedagogical Action Selection (***PAS***) and identified three general approaches to produce them in intelligent tutoring systems that use Bayesian networks: alternative strategies, diagnostic strategies, and decision-theoretic pedagogical strategies (ibid., p 132).

For us a didactical decision is to propose the best feedback and depending on the diagnosis results. This decision means a choice between different possible hypotheses based on didactical analysis. We use a decision-theoretic approach in order to model this process. The decision-theoretic strategy is used in some ITSs to select tutorial actions that maximize the expected utility. The systems CAPIT [14] and DT tutor [16] use this strategy.

CAPIT is a system for learning capitalization and punctuation in English. To decide two kinds of next feedback (next problem selection, error message selection) this system uses the utility function, which is based on the number of errors that the student made [14]. DT tutor also uses a decisional model: "*For each tutorial action alternative, the tutor computes (1) the probability of every possible outcome of that tutorial action, (2) the utility of each possible outcome in relation to the tutor's objectives, and then (3) the alternative's expected utility by weighing the utility of each possible outcome by the probability that it will occur. The tutor then selects the action with maximum expected utility with utility function*" [16]. In DT tutor, many factors related to the student (their morale, behaviour, etc) have an influence on expected utility. To propose the next feedback, DT tutor chooses first the theme where the feedback is focused and second the type of feedback (help, hint, positive or negative feedback). DT tutor is implemented in two learning systems, calculus and elementary reading.

A further difference between these previous works and our approach is that the decision feedback models proposed previously are not based on the nature of the control knowledge; in our case we would like to center the feedback on the knowledge control dimension (knowledge that allows the users to validate their actions during the process) and to take into account the knowledge control specificities (pragmatic, declarative and perceptive-gestural). Another difference is that, in our learning environment, there are no well defined solutions and thus it is not possible to define a priori, a list of actions as expected feedback. Because we have some characterised resources in our environment, the feedback is built in several steps; it has a target, an objective, a form and content. It is created with a decision-making process based on several PAS (Pedagogical Action Selection). In each step of the process, the chosen strategy corresponds to the degree of dependency of the step in relation to the domain knowledge.

Finally the factors considered in our system must be the parameters that can be established by researcher. Indeed, this is multidisciplinary research that evolves and the system must adapt to the evolution of didactic and medical analysis. Different feedback hypotheses must be able to be tested.

3. THEORETICAL FRAMEWORK AND DIDACTICAL HYPOTHESIS

According to research in cognitive psychology and didactics, the learner/situation interaction can be modelled as a problem-solving process that engages itself different processes, tightly linked and recurrent: identification of the situation, planning, action, control of actions' effects, regulation. The crucial role of control elements in this process has been pointed ([1],[17]), allowing the subject to decide whether an action is relevant or not, or to decide that a problem or sub-problem is solved.

This framework has some important consequences on our work for our objectives related to the design of a feedback system:

- It is necessary to *choose characteristics of problems* that will conduct to the right processes of learning according to professional objectives and to learner's state of knowledge. This, in turn, leads to the necessity to diagnose learner's knowledge, and interpret this diagnosis to be able to provoke targeted learning through learners' actions and controls on problems. Thus, one objective of *the feedback system is to consider* is not only the actions but also *the controls brought into play by the learner during the problem solving activity.*
- It is necessary to *distinguish* and consider both, *the result* (a punctual state of the problem, intermediate or final) *and the problem solving process*. We thus adopt a continuous approach of diagnosis and learning process.

Besides, we argue that is necessary to distinguish the controls characteristics. These categories are related to the way that knowledge can be validated, and therefore, built. In the case of orthopedic surgery we identify three categories: declarative, pragmatic and perceptive/gestural. The first category, declarative knowledge, corresponds to shared knowledge, constituting a common reference for professionals. It can be expressed, formally, and serves communication, discussion, exchanges. The second, pragmatic, is partly expressible, and is linked to individual experiences and situations. The third concern the perceptive and gestural (technical gesture like surgical gesture) part, hardly expressible and embedded in particular situations.

These are not the same that the classical division of knowledge between declarative and procedural. For example, part of procedural knowledge is validated in a declarative manner (is a reference for professionals and transmitted in a declarative way), part is validated in a pragmatic manner (by experience) and can also be validated in a perceptive-gestural manner (what is seen, felt). This second kind of activity is ill defined task, i.e. there are not clear strategies for finding solutions at each step of the problem solving process.

3.1 Characterization of didactical hypothesis' factors

Based in previous framework our objective is to propose a feedback system able to take into account the didactical hypothesis.

First of all and as explained above, each control element of knowledge is labelled according to its nature: declarative, pragmatic, or perceptual/gestural. Then, concerning knowledge related to the user's action, it is labelled according to the moment it appears in the resolution process and according to its possible validity.

This last element necessitates some clarification: knowledge elements are diagnosed by the environment, according to user's set of actions and knowledge domain of validity, as being mobilized (brought into play) in a valid situation state (inside its validity domain), not mobilized or mobilized in an invalid situation state (outside its validity domain).

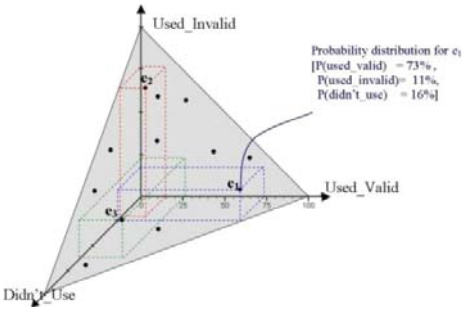

Figure 1. Result of knowledge elements diagnosed

The output can be considered like a tri-dimensional space (shown in Figure 1), where each knowledge element (e_i), in our case controls, has a probability distribution according to their state (invalid, valid, or not-used). In the given example, the knowledge element e_1 is brought into play in a valid manner with a probability of 73%.

Based in this result we made choices concerning the best relevant type of feedback to be provided to the user, according to previous diagnosed elements.

Thus, to produce epistemic feedback, the didactical analysis is based on the characteristics (state, order, type, etc.) of the control knowledge element and the classes of situations available. Also, to integrate the adapted dimension the feedback process has to take into account the student knowledge (the diagnosis result) and the characteristics of the learning environment (resources manipulated by the student and the characteristics of the problem).

4. THE PROCESS TO PRODUCE AN ADAPTIVE EPISTEMIC FEEDBACK

This process has four related steps. First, our decision model chooses the knowledge element(s), proposed by the diagnosis system, which will target the feedback. Second, it determines the feedback's apprenticeship objective for the chosen target. Third, according to the target and the objective, it determines the relevant form of feedback from the existing forms in the learning environment. Finally, according to the form, the decision model formulates the feedback by defining its content. The process is conceived from objectives and didactical hypothesis, summed up in §3, which are represented like parameters in the system.

In the next paragraphs, we describe each step in detail.

4.1 Chose the target of the feedback

This step can be shown as the selection of knowledge elements which are target by the feedback. The selection is influenced essentially by the knowledge diagnosis results and the controls' characteristics. In our case the knowledge elements are the controls which are brought into play during the problem solving activity. At each student action a list of controls were diagnosed. The results of one step can be seen like in the Figure 1. This diagnosis system is described in Chieu et al. [4].

We use influence diagrams to represent this step of decision. It is used to represent and to calculate the decision-making in several applications [6], [7]. In the influence diagrams there are decision nodes and utility nodes as well as chance nodes.

We have chosen this approach because it allows making decisions under uncertainty. Indeed, the learner's state of knowledge, produced by the diagnosis, will be deduced from learner actions with a degree of uncertainty, so our model has to generate the best feedback according to this input.

In our model (Figure 2) there are knowledge nodes (the oval nodes that represent the result of the diagnosis), an apprenticeship utility node (hexagonal node) and target decision node (rectangular node with the list of candidate elements or knowledge to be targeted). The inference in this diagram allows selecting a knowledge element as target. Indeed, the result of the inference gives the values of the utilities for each knowledge element, the highest one will be the targeted element for the feeback.

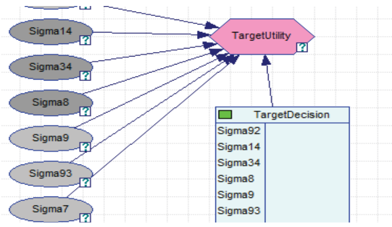

Figure 2. The influence diagram for target decision

To apply the inference in the diagram, we defined a function that models the preferences from an apprenticeship point of view, which is the utility function. The preferences will be described numerically under the notion of utility U, where U(a1)> U(a2) means the decision-maker prefer action a2 compared to the action a1.

In our case the apprenticeship utility function, Uapp(c, E), allows us to calculate the a priori utility to focus feedback on an element knowledge of a candidate (c) by taking into account the set of knowledge elements (E). Then, the inference in the influence diagram calculates the estimated utility for each candidate according to the diagnosis results. In other words, the utility function initializes the calculation in the influence diagram and then the inference algorithm deduces the decisions.

As we can see, in the previous figure the diagram is very simple; our contribution is basically in the definition of the apprenticeship utility function that takes into account the didactical hypothesis, which we explain in the next paragraphs

4.1.1 Apprenticeship utility function

This utility function allows initializing a priori utilities according to the factors that influence the target decision. We identified some factors as the element state and the element characteristic:

1. Element State is the diagnosis result. It represents the manner of using the knowledge element in the problem-solving process: Used-valid, Used-invalid, not-used.
2. Element Type, it is linked to the validation criteria for each identified knowledge, like explained after, in our

current Teleos example it can be "declarative", "pragmatic" or "perceptive-gestural";

3. Element Order represents the step of problem-solving in which this element intervenes. An element can intervene in several problem-solving steps, for example the control knowledge related to the profile X-ray can intervene in several steps of the activity;
4. Element Context indicates the context of problem-solving in which this element intervenes. It can be 'general' or 'particular'. For example, in the case of surgical domain, some steps and knowledge control elements could be especially for the scoliosis intervention.

From all of these factors we define in the equation (1) $U_{app}(c, E)$ the utility to choose a candidate element, ***c,*** as feedback target in taking into account the set of knowledge elements, ***E***, as the sum of all the utilities related to each factor.

$$U_{app}(c,E)=\alpha\cdot U_{state}(c,E)+\beta\cdot U_{Type}(c)+\gamma\cdot U_{order}(c)+\delta\cdot U_{context}(c) \quad (1)$$

In our didactical hypotheses, these factors do not have the same weight in influencing the choice of the target. Thus, we attribute to each factor a priority variable (α, β, γ, and δ), which represents its weight in the utility calculation.

We define in the equation (2) the utility of choosing a candidate ***c*** as a target according to its state $U_{state}(c, E)$, as the sum of utilities for each pair of candidates ***c*** and element $\boldsymbol{e_j}$ in ***E***; n is the number of knowledge elements of the set E.

$$U_{state}(c,e_1,e_2,\ldots,e_n)=\sum_{j=1}^{n}U_{State}(c,e_j) \quad (2)$$

In addition, we define the state utility in the table for each pair $U_{state}(c, e_j)$. The values are defined according to didactical hypotheses and the domain of knowledge.

For example, the didactical hypothesis "*it is more important to focus the feedback on an element that is used in an invalid way than to focus it on an element that it didn't use"* is represented by a value where Ustate(c = "used_valid", e) ≥ Ustate(c = "not-used", e). In other words, we propose one utility state table that allows selecting between two elements situated in the diagnosis results space (shown in Figure 1) according to the chosen didactical hypothesis.

The definition of the type utility $U_{type}(c)$ from didactical hypothesis can be "*it is more important to focus the feedback on a declarative element than to focus it on a pragmatic one*". We express this by giving to declarative elements the higher value of utility. In this example, the $U_{type}(c) = 3$ if c is declarative and 2 if it is pragmatic. In the present implemented version, the system doesn't take into account the perceptive-gestural knowledge because the didactical analysis is ongoing, but it is modelled to integrate it in an easy and modular manner.

We define the utility order: Uorder(c), from the didactical hypothesis "it is more important to focus the feedback on an element appearing in a primary stage of the solving than to focus it on an element appearing in later stages". Thus, it is possible that an element appears in several stages. We define the utility order in equation (3); m is the number of steps where this element appears and O(c) is its order. The first time of the control *i* is identified Oi(c) = 1.

$$U_{order}(c)=\sum_{j=1}^{m}\frac{1}{O_j(c)} \quad (3)$$

We define the nature utility $U_{nature}(c)$ from the didactical hypothesis as follows: "*it is more important to focus the feedback on an element appearing in the solving of a general problem than to focus it on an element appearing in a particular context*". Like the Utility type function case, we express this by giving a higher value of utility to the nature target chosen (in this case if c is general $U_{context}(c)= 2$).

According to these considerations, we have defined an algorithm that calculates the apprenticeship utility function and initializes the utility table from a set of knowledge elements with their characteristics. In this algorithm we create, first of all, the coefficients' matrix « *coeff* » in relation to the number of knowledge elements (k), and then we calculate the state utility table for each candidate. It is calculated based in formula 4, where *k* is the number of the column, j is the possible state of the knowledge element (used-valid, invalid or not-used) and *Hypo* is one of the didactic vectors A,B or C related to the state of the targeted candidate in column *k*

$$ValeurUtilitéEtat[k]=\sum_{j=1}^{3}Coeff[j,k]*Hypo[j] \quad (4)$$

This algorithm needs to be to running only once, after settle the didactical hypothesis. The inference in the influence diagram then uses probabilities resulting from the diagnosis and then calculates utility values to infer the estimated utility for each element. Finally, the target for the feedback is the element that has the maximal estimated utility value (Figure 3) calculated. It is possible to have some elements with the same maximal utility.

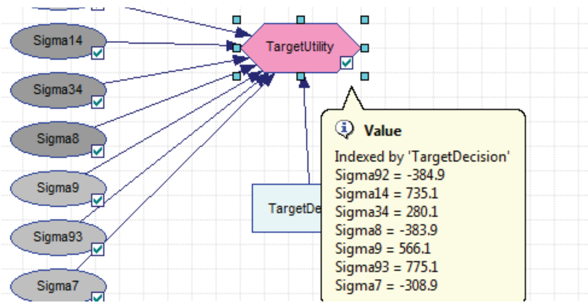

Figure 3. Inference Diagram decision result

As we presented before, we have chosen to represent all didactical hypotheses as parameters in the utility function. This choice makes our model flexible to add or modify didactical hypotheses. For example, for the factor "Type of Knowledge" if the didactical hypothesis is "*it is more important to focus the feedback on an pragmatic element than to focus it on a declarative one*", then it is sufficient to give the parameter that represents the utility for an pragmatic element a value higher than the utility for a declarative element $U_{type}(c=pragmatic)> U_{type}(c=declarative)$.

4.2 Choose the objective of the feedback

After choosing the target, the decision model determines its feedback objective in order to give, from the learning point of view, a semantic to the feedback intention. In our model we distinguish several feedbacks. Indeed, if the target knowledge is diagnosed (with a higher probability) as 'brought into play in an invalid manner' (BPI) the feedback is not the same than if this target knowledge is diagnosed as 'not brought into play' (NBP).

We have defined a procedure that determines the feedback objective by applying an analysis on the target element state. The principle of this procedure is that it segments the diagnosis space into several zones, and it attributes an objective to each zone. Then, the feedback objective corresponds to the zone in which the target element is situated. This step permits to pass from an uncertain state of knowledge to fixed objectives of learning. The number of segmented zones and the objective for each zone is customizable in our model.

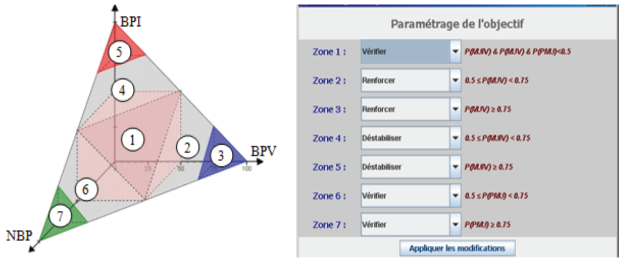

Figure 4. Example of segmentation of the knowledge elements space to determine the feedback objective

In this example, if the knowledge element is in zone 1 ("*if P(NBP) – P(BPI) > 0.25 and P(NBP) – P(BPV) > 0.25*") then the feedback objective is to "verify" if the targeted knowledge is understood by the learner. The possibilities proposed for the feedback objective are: verify, reinforce and destabilize. The meaning of *verify* feedback is to propose a type of feedback to improve the diagnosis related to a set of knowledge targeted elements (for example, proposing another problem where specific targeted knowledge has to be mobilized). The idea of the *reinforce* feedback is to support the user in relation to the targeted knowledge elements (for example a positive feedback, a closer clinical case that was studied or solve another problem where the targeted knowledge could be used). Finally, *destabilize* feedback has the objective to show that the targeted knowledge is used in an invalid manner in these kinds of problems (by explaining the right way in the course, proposing a counter example from the clinical case database or proposing another problem where if the knowledge is used, the result could be wrong)

4.3 Determine the feedback form

In this step, the decision model chooses the most relevant form of feedback linked to the type of the target knowledge element and the feedback objective (*reinforce, verify, destabilize*).

Here the idea is to associate one kind of feedback form to the feedback objective and the type of the targeted knowledge element. In this step we need to consider the resources proposed to the student. Indeed more and more TEL system proposes several resources to the student. For example if the environment has a wiki with concepts we can associate it to a form of feedback when the targeted knowledge element is declarative and the feedback objective is to reinforce.

This association is a simple table where we can match the resources with a pair <type of knowledge, feedback objective>.

4.4 Determine the feedback content

The content is essentially related to the form of feedback. Here the objective is to determine the content of the feedback in relation to the feedback form. For example if the feedback form is a wiki with concepts the content has to be related with the targeted knowledge element.

This step is not generic, it depends on the kind of feedback forms that the TEL system has. For this reason this step will be more detailed in the next section where we explain the case study where we implemented the feedback process.

5. THE TELEOS SYSTEM EXAMPLE

The analyzed procedure is about surgical orthopaedic percutaneous (without incision) operation. It is developed in [21]. It could be summarized as follows: The surgeon first inserts a pin in the bone through the skin. S/he makes the pin progress in the bone, taking several X-rays to validate the pin's course at different steps of its progression. The X-rays allow him or her to "reconstruct" a complete vision of the position of the pin, in relation to the bone. If s/he recognizes any problems in those views, s/he restarts the operation process, taking another pin and correcting its entry point and/or direction. Until now we have analyzed the sacroiliac screw operation and the vertebroplasty. The description procedure does not have to be complete and well-defined but the goal is to extract from the diversity of each particular situation, the significant controls elements, from a learning point of view, of the surgical procedure.

The analysis, made in [21], allows us to identify crucial aspects of the surgical procedure. We identified primarily that the pin's positioning is the most important part of the procedure, the definitive screw being placed along this pin. Secondly, we notice the crucial role of X-ray controls. As the surgeon cannot directly visualize the operating area, he has to interpret his gesture through these controls. This necessitates two levels of interpretation. On the first level, the surgeon has to ensure that the X-ray is valid (i.e. being oriented in order to represent what it is intended to represent); on the second level, the surgeon can look at the validity of the pin's position according to anatomical criteria on the X-ray.

Table 1. Examples of knowledge controls for sacroiliac screw

Control Type	Control elements of knowledge	Domains of validity
declarative	The pin's trajectory must be completely intra-osseous	all
declarative	If the pin is well positioned then the pin appears as a point on the profile X-ray	PB, PC, PE
Pragmatic	If the pin would become extra osseous by being pushed in S1, 1cm after the median line, then it can be stopped at the median line	PC, PD
Pragmatic	If the pin would become extra osseous, then it can be stopped just 1cm after having reached S1	PA,PD,PF
Perceptive-gestural	If the pin was in the sacroiliac and the resistance force decrease then the pin would become extra osseous	All

Thus, we identified the control knowledge elements, which are related to surgeons' actions during the intervention, they allow surgeons to validate their actions; some examples are shown in Table 1. The controls have a domain if validity, i.e. they are valid for a set of problems. The control type is also identified: it could be declarative, pragmatic, or perceptive gestural.

5.1 TELEOS SYSTEM

We have developed a modular architecture. Each module is built in relation to the knowledge learning constraints [10]. The learner interacts with the following modules: Semantic Web Courses, Simulator, and Clinical Cases. We introduce briefly these three modules in the next section. The decision-making model uses these modules and the result of the diagnosis to build the feedback. The diagnosis model will not be described in this paper. The result will show in the Figure 1.

5.1.1 Simulator for orthopaedic surgery

The last implementation version is explained in a previous paper [12]. Two surgeries were implemented in this last version: the vertebroplasty and the sacroiliac screw.

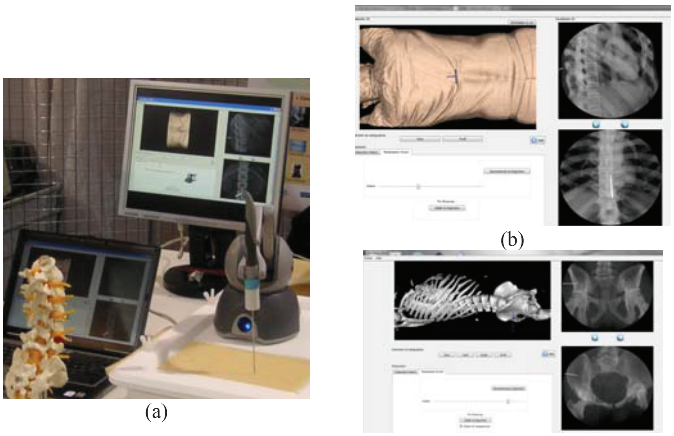

Figure 5. Haptic interface (a). Graphical interface during the pin trajectory (b). Graphical interface when the trajectory is validated by the user (c).

Regardless of the simulated operation, the TEL system gives to the learner the opportunity to train himself and practise a surgical operation thanks to several functionalities: Choosing the type of patient and the type of operation; visualizing in 3D the tool and the patient model; Adjusting the position and the incidence of the fluoroscopic image intensifier; Drawing the cutaneous marking on the body of the patient model; Producing and visualizing radiographies; Manipulating the surgical tool through a mouse or through haptic interface; Verifying the trajectory in a 3D bone model when it has been validated (Figure 5). In this paper we are focused on the pelvis operation.

In the previous figure we can see on the right of the graphical interfaces (b and c), two 2D images representing the last two radiographies produced by the user. In the top left hand corner, there is the 3D model of the patient, and the surgical tool, the user is able to see the 3D bone model only when the trajectory is validated.

5.1.2 Clinical cases database

The role of the Clinical Case agent is to illustrate the consequences of a proposed trajectory. It is a database where we can find pertinent information related to different phases (before, during and after the operation).

Figure 6. Clinical Case with data from one operation

For example, one clinical case may have some x-rays before the operation (**Figure 6**, right side), some films of the gesture during the operation and some x-rays and data describing the post-operatory information (the position of the bone, the state of the bone, etc… left side **Figure 6**). This Clinical Case Database could be useful to show, for example, trajectories that have consequences in the post-operatory period (there may be a problem with the fracture reduction because the trajectory with the pin is too short, for Instance).

5.1.3 Online Courses

We have an online course (at http://www-sante.ujf-grenoble.fr) that explains the declarative knowledge (anatomy, surgical procedure, tools, etc.) about sacroiliac percutaneous screw placement. It is based on online courses and academic documentation, and is improved by interaction between the didactical expert and the surgeons.

For this part we use ontology with a set of rules based in OWL language. We have developed a semantic web module, with more than eighteen web pages, which have metadata based on ontology. This module proposes not only syntactic links, but also semantic ones; it allows the redirection to precise and relevant chapters of the online course. The implementation of this module is explained in previous work [8].

5.2 ADAPTIVE AND EPISTEMIC FEEDBACK PROCESS

Like introduce in the paper the implemented feedback process is a delayed feedback, i.e. the TELEOS system propose a feedback at the end of the activity. The result of the process can be to solve another problem on the simulator, to consult a particular webpage on the online course or to consult one specific clinical case in the database.

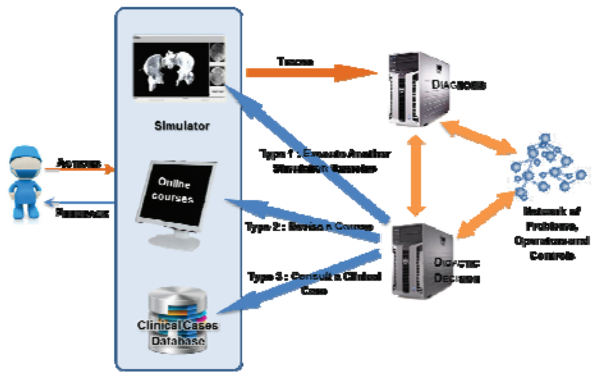

Figure 7. Kinds of feedback in TELEOS system.

Because the two first steps described previously are generic, we don't explain them in detail here. In the step three we propose a simple table interface where the didactical or pedagogical user can propose the match between the resource (simulator, clinical case and web course) and the pair type of knowledge (declarative, pragmatic, perceptivo-gestural) and feedback objective ((*reinforce, verify, destabilize*). We can choose one or several forms for the same pair <type, objective>. For example, the pedagogical user was proposed the clinical case and the simulator to destabilize the pragmatic knowledge.

For the step 4 we need to consider the specific form of the feedbacks. In our case we have three forms of feedback (online web course, simulator, and clinical database) and to find the inquired form we do not apply the same process. One example of possible feedback is shown in the next figure:

In the case of the form 'consult part of web courses', the content represents the links to the appropriate pages. It is made by sending keywords related to the target element to a semantic web model [8]. This feedback receives the knowledge elements to be considered, which are analyzed by the java program, using the ontology, and finally it produces a web page with a set of links to the online course, which are related to the targeted knowledge. The Java Engine code uses the open source tool Jena which offers libraries to work with OWL files. In the case of the sacro-illiac surgical operation, our system is based on two ontologies, one related to the pelvis anatomy, which is built on Standford university anatomy ontology [2], and the other one is related to the screw placement procedures, which we built and validated with our experts.

For example if we give the knowledge element 'Outlet radio control', which is in relation with anatomical ontology, the java engine finds the classes related to these knowledge elements and produces a set of links which come from the online course.

The calculation of the content for the forms 'clinical cases' and 'simulator' is made according to the target and to the feedback objective. For the form 'consult a clinical case', it represents the relevant case like a query in a database.

Finally, for the form 'solve another problem with the simulator', it represents the relevant problem to solve. The design can be made by applying inference algorithms in the Bayesian Network (that represents the knowledge domain) or by a decisional theoretical approach to select a closer problem [15]. In the present version we find the problem that has the most common didactical variables (kind of fracture, the hardness of the spongy bone) with the solved problem.

5.3 Evaluation and discussion

The evaluation of the didactical decision process was achieved in several steps. Because the utility function is additive, we evaluated first the dominance between different modelled factors and second we made a sensitive analysis to study the adaptability of the model. Moreover, we made an evaluation to study the behaviour of the system in relation to the expert's propositions. Here we present this last evaluation. The others evaluations show that, firstly, small changes in the assigned probabilities lead to different decisions of feedback target. It means that if there is one small change then the result of the calculus of the target feedback could be radically different. Secondly, the sensitivity level can be adjusted according to the weight given to the element state factor.

The aim of the comparison with expert proposition is to verify and refine the model in relation to the human didactical feedbacks. Here the input is the simulated diagnosis of learner's state of knowledge (e1 [BPI 0.7, BPV 0.17, NBP 0.13], e 92 [BPI 0.65, BPV 0.23, NBP 0.12], etc) and the output is the feedback proposed (Consult the parts of the course 'entry point related to skin marks', propose a problem, with a disjunction, to solve in the simulator, etc.). These scenarios are run by an expert in didactics and by our didactical decision system, afterwards they are compared.

Because in our model the didactical hypotheses are customizable, the parameters have to be calibrated by an expert (in didactics for example) before using it. To make the adjustment of these parameters easier, we developed some interfaces and we also proposed a questionnaire that contains multiple-choice questions, (associate to didactical hypothesis) and we associate with each choice a possible value of the parameter. Therefore, the answers to this questionnaire allow initializing the calculation in the model.

One example of scenario given to the experts is "after radio outlet, a student does not takes Inlet radio and modifies its trajectory in the wrong direction (the pin was placed a little low on the outlet, it starts and moves the point of entry down). The declarative control e93 (coupling outlet / inlet) comes NBP 30%, the declarative control e19 (risk of passing through the hole of the sacrum because too low on outlet) is BPV 50% and the pragmatic control e18 (link outlet position / position of patient) is 75% BPI". One expert proposition was: "propose the web page linked to the inlet/outlet coupling and propose an exercise related to the 2D and 3D association".

In relation to the configuration of the system, the answer of the questionnaire shows us a dependent relationship between the state of the knowledge elements and its characteristics while in our model these factors are independent (it is an additive function). For example, the question about what is more important to target a "not-valid knowledge" or a "not used knowledge", the expert answer depends on the type of the knowledge (declarative, pragmatic, etc.).

In addition, regarding the output proposed by the expert, the results show that the system is able to produce relevant feedbacks for each scenario. Furthermore, some feedbacks are not exactly the same as the expert feedbacks. We identify two reasons for these differences. Firstly, the present model selects as target one (or some) element(s) that has(have) the maximal value of estimated utilities but in the expert propositions, the feedbacks can be related to some elements with positive values of estimated utilities and related as well to the elements with the maximal value. Secondly, the present model is not able to propose a sequential set of feedbacks (for instance, the expert proposes that feedback 1 follows feedback 2). In fact, the present model is able to take the historical dimension with the evolution of the probabilities, but it does not yet treat the historical dimension related to the previous feedback

6. DISCUSSION

This system had to support an explicit representation of pedagogical and didactical hypotheses and, from a computer architecture point of view; the system had to be separated from the other modules. These choices are related to the idea of proposing a normative system, able to evaluate separately and also to allow the investigation of some didactical hypothesis to generate the feedback.

The decision model thus integrates didactical hypotheses in order to represent the decision-maker's preferences. These didactical hypotheses are customizable; this choice makes our model dynamic and partially generic. Also, this kind of model intends to allow multidisciplinary work in order to investigate pedagogical feedback.

From the epistemic dimension of the feedback point of view, the system cannot be completely generic but the design allows identifying the generic steps from the knowledge analysis dependant steps.

In relation to the adaptive dimension of the feedback, the system is able to adapt the feedback to some epistemic considerations about the user and the available resources. Indeed, this adaptive dimension takes into account only the knowledge factors. It doesn't take into account other factors like the morale or attention. Also, as pointed out by Woolf ([23] p. 133), it is necessary to integrate different teachers' strategies: *A single teaching strategy was implemented within each tutor with the thought that this strategy was effective for all students. However, students learn at different rates and in different ways, and knowing which teaching strategy (...) is useful for which student would be helpful. This section suggests the need for multiple teaching strategies within a single tutor so that an appropriate strategy might be selected for a given student".*

The reliability of our model depends on the accuracy of diagnosis results and the best set of parameters. Here it is also necessary to refine the model using real data in order to improve its structure, the conditional probability and the decision factors by using a method of automatic learning from data.

Moreover, the evaluation indicates that it seems necessary to consider not only the history of the student activity but also the dynamic aspect linked to the decisions. Indeed, in the classical approach the decision is in relation to the predictive aspect of the student model ([16], [2]) i.e. it calculates the consequences of the feedback on the predictive student model. However, it appears that the dynamic aspects concern not only the student factors but also the resources or the decision itself.

The data collection seems to be the perspective's keystone in order to improve the present model but also to go forward in this kind of research. However, the data to be collected it is not only the classical data in the domain of learning systems, i.e. the data from the student, but also the data linked to the feedback decision. This kind of collection will be more centred on the analysis of the decision process for the feedback production.

7. REFERENCES

[1] Balacheff N., Gaudin N. (2010) Modeling students' conceptions: The case of function. *Research in Collegiate Mathematics Education*, Volume 16, 183-211.

[2] Chieu, V., Luengo, V., Vadcard, L., & Tonetti, J. (2010). Student modeling in complex domains:Exploiting symbiosis between temporal Bayesian networks and fine-grained didactical analysis. *Journal of Artificial Intelligence in Education.*.

[3] Foundational Model of Anatomy, S. (2006). *Research Projects, Foundational Model of Anatomy*. Retrieved 2008, from http://www.smi.stanford.edu/ (Research Projects, Foundational Model of Anatomy).

[4] Fournier-Viger, P., Nkambou, R. & Mephu Nguifo, E. (2010). Building Intelligent Tutoring Systems for Ill-Defined Domains. In Nkambou, R., Mizoguchi, R. & Bourdeau, J. (Eds.). *Advances in Intelligent Tutoring Systems*, Springer, p.81-101.

[5] Fournier-Viger, P., Nkambou, R., Mayers, A., Mephu Nguifo, E & Faghihi, U. (2012). Multi-Paradigm Generation of Tutoring Feedback in Robotic Arm Manipulation Training. *Proceedings of the 11th Intern. Conf. on Intelligent Tutoring Systems* Springer, pp.233-242.

[6] Horvitz, E., Kadie, C., Paek, T., & Hovel, D. (2003). Models of attention in computing and communication: from principles to applications. *Commun. ACM* , 52-59.

[7] Kabanza, F., Bisson, G., Charneau, A., & Jang, T. (2006). Implementing tutoring strategies into a patient simulator for clinical reasoning learning. *Artificial Intelligence in Medicine* , 79-96.

[8] Luengo, V., & Vadcard, L. (2005). Design of adaptive feedback in a web educational system. *Workshop Adaptive Systems for Web-Based Education: Tools and Reusability*. In International Conference on Artificial Intelligence in Education. Springer-Verlag.

[9] Luengo, V., Vadcard, L., Dubois, M., & Mufti-Alchawafa, D. (2006). TELEOS : de l'analyse de l'activité professionnelle à la formalisation des connaissances pour un environnement d'apprentissage. *IC 2006.*

[10] Luengo V. (2008) Take into account knowledge constraints for TEL environments design in medical education. *ICALT* 2008.

[11] Luengo V. (2009). *Les rétroactions épistémiques dans les Environnements Informatiques pour l'Apprentissage Humain. Habilitation à diriger des recherches.* Habilitation à diriger des recherches. Université Joseph Fourier., 2009.

[12] Luengo V., Larcher A., Tonetti J.. (2011) Design and Implementation of a Visual and Haptic Simulator in a Platform for a TEL System in Percutaneuos Orthopedic Surgery. *Medicine Meets Virtual Reality* MMVR, 2011.

[13] Lynch, C., Ashley, K., Aleven, V., & Pinkwart, N. (2006). "Defining Ill-Defined Domains; A literature survey." *Proceedings of the Workshop on Intelligent Tutoring Systems for Ill-Defined Domains at the 8th International Conference on Intelligent Tutoring Systems* (p. 1-10).

[14] Mayo, M., & Mitrovic, A. (2000). Using a Probabilistic Student Model to Control Problem Difficulty. *Intelligent Tutoring Systems* (pp. 524-533). Biarritz: Springer-Verlag.

[15] Muldner, K., & Conati, C. (2007). Evaluating a Decision-Theoretic Approach to Tailored Example Selection. *IJCAI*, (pp. 483-488).

[16] Murray, R., VanLehn, K., & Mostow, K. (2004). Looking ahead to select tutorial actions: A decision-theoretic approach". *International Journal of Artificial Intelligence and Education* , 235-278.

[17] Schoenfeld, A. (1985). *Mathematical Problem Solving*. New York, NY: Academic Press.

[18] Shute, V. J., & Zapata-Rivera, D. (2012). Adaptive educational systems. In P. Durlach (Ed.), *Adaptive technologies for training and education* (pp. 7-27). New York, NY:Cambridge University Press.

[19] Simon, H. A., "The Structure of Ill Structured Problems," *Artificial Intelligence* **4**, (1973), 181-201.

[20] Stamper, J., Barnes, T., and Croy, M. (2010) Enhancing the Automatic Generation of Hints with Expert Seeding. Proceeding of ITS2010. vol. II, pp. 31-40. Berlin, Germany: Springer Verlag.

[21] Tonetti J., Vadcard L., Girard P., Dubois M., Merloz P., Troccaz J. (2009). Assessment of a percutaneous iliosacral screw insertion simulator. *Orthopaedics & Traumatology: Surgery & Research, Vol 95* n°7, 471-477.

[22] Wagner, R., Sujan, H., Sujan, M., Rashotte, C., & Sternberg, R. (1999). Tacit Knowledge in Sales. In S. R. J., & H. J. A., *Tacit Knowledge in Professional Practice: Researcher and Practitioner Perspectives* (pp. 155–182). Mahwah, NJ: Lawre.

[23] Woolf, B. P. (2009). Building Intelligent Interactive tutors : student-centered strategies for revolutionizing e-learning. Burlington, MA, USA: Elsevier