A Framework for Affective Intelligent Tutoring Systems

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***Abstract*— In social context, emotions play a prominent role in verbal and non-verbal communication. With their multi-modal perception, the aptitude of an interlocutor in identifying them, through a diversity of behaviors such as face movements, gestures, speech, is a fundamental aspect as judgment and decision making are influenced by mood, feelings, which facilitates human adaptation and social integration. In a cognitive activity such as learning, communication (between learners and tutors) is one of the fundamental issues, and its quality may influence the learning. Therefore, learning process implies cognitive aspects as well as socio-emotional aspects: in real world, teaching also implies to observe the student's affective behavior in order to detect affective responses which can express interest, excitation, confusion, etc. and suggest a review of the actual interaction flow. This paper presents an Intelligent Tutoring Systems (ITS) architecture equipped with emotional management capabilities which make it possible the capture of student emotions during learning and affective response to learners' actions. The result system called AITS (Affective Tutoring System) could efficiently adapt content planning, learning/tutoring strategies and even tutoring dialogues based on affective and cognitive data.**

***Index Terms*— Intelligent Tutoring Systems, Emotional Agent, Student Modeling, Tutoring Feedback**

I. Introduction

Our interest in the role of emotional agents integrated in Tutoring Systems is motivated by the social cognitive theory suggesting that learning takes place through a complex interplay between both cognitive and affective dimensions [1]. Researches in cognitive sciences argue that emotions enable people to communicate efficiently by monitoring and regulating social interaction [2], by evaluating and modifying emotional experiences [3].

Tutoring Systems are computer-based learning systems that seek to reflect new methods of teaching and learning based on one-to-one interaction. To be classified as "intelligent", they must present "human-like" tutoring capabilities, that means to be able to adjust the content and delivery of the lesson to the students' characteristics and needs by analysing and/or anticipating theirs responses and behaviours. So emotions appear to be essential for human intelligence rationality in human-computer interaction.

In order to promote a more dynamic and flexible communication between the learner and the system, we integrate two adaptive emotional agents in a multi-agent AITS. The first one allows the tutor to express emotions in response to the student's actions. An emotional tutor, called Emilie-1 has been successfully integrated in a learning environment for on-line teaching of science. The second one aims at capturing and managing the emotions expressed by the learner during a learning session. This agent (Emilie-2) works according to a pedagogical loop which includes the following actions: 1) capture, extraction and recognition of emotions through a given emotional channel; 2) analysis, diagnosis and interpretation of the recognized emotions; 3) remediation through relevant pedagogical actions.

This paper is organized as following: Firstly, we present an architecture of AITS with emphasis on emotions management components. Secondly, we present the two adaptive emotional agents (Emilie-1 and Emilie2). Some details on the implementation of Emilie-2, mainly its emotions recognition component (perception layer) are also presented.

II. Architecture of AITS

This research focuses on emotional management in learning context. We believe that taking the learner emotional state into account can enhance the learning's quality. Also, tutor feedbacks could be improved if the tutor can express emotions [4]. Hence, our research aims at extending both the learner and the tutor models which emotional aspects. This extension is done by integrating two emotion management agents, one for the tutor's emotions management and the other for the student's emotions management. Figure 1 presents the multi-agent architecture of AITS which includes those two emotional agents. In this figure, the learner's model represents both his cognitive state (knowledge, skills and performances' history) and his affective state (mood, emotions and psychological profile). We could also see that a specific agent manages the cognitive state: the profiler. This agent updates the acquired knowledge, skills and performances of the learner, and

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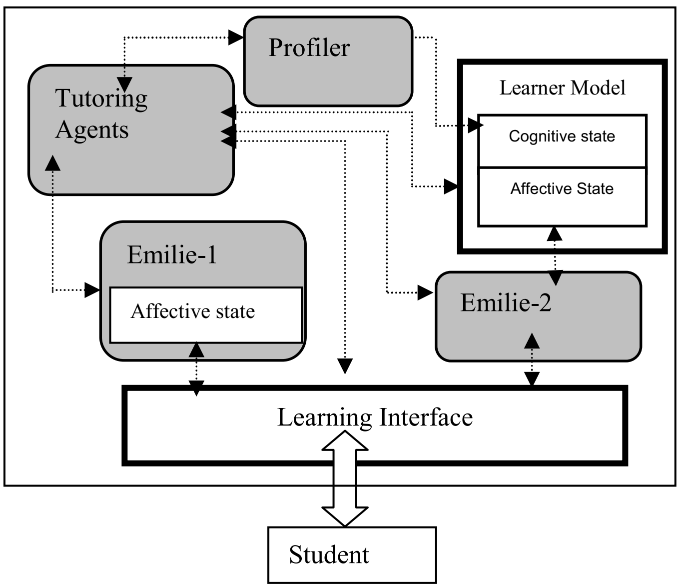
maintains the cognitive model integrity. It also helps the diagnosis of knowledge or skills incorrectly learned, or missing, and permits remediation with the help of tutoring agents [15].

The affective state contains short-term information (resp. medium and long-term), which corresponds to emotions (resp. mood and psychological profile) of the learner. Emilie-2 manages this part of the model. Tutoring agents are the agents that contribute to the training: a planner for the selection of relevant learning activities, a coach which helps students during problem solving activities, etc.

Fig. 1. System architecture



During the learning process and when interacting with the learner, some tutoring agents may want to include emotional dimension. Thus, they use Emilie-1 which is able, within a specific activity, to translate through a character (2D or 3D), the emotions of the tutoring agent. It has to be aware of the concerned task and of the desired emotional reaction (by the designer or the concerned tutoring agent). The emotional state of Emilie-1 is a short-term memory which represents the current emotional reaction. The action is carried out through the virtual laboratory (learning interface) which includes interactive tools (objects and resource) related to the content.

III. Expressing Emotion Using Emilie-1

To be able to compute emotion, a computational model of emotion is needed. Most of the existing emotional models are based on one of the following: Minsky's paradigm [5] and the Ortony Clore and Collins (OCC) theory of emotions [6]. The most popular emotional models include: Fungus eater model [7], OCC model, Cathexis [8] and Roseman's model [9, 10]. Our approach uses OCC model. Other systems that use OCC model are: the Affective Reasoner [11], Emile [12] and STEVE [13].

Figure 2 shows Emilie-1's basic architecture. Since there are an extremely large number of different application domains for ITS, all emotion-handling functions are domain independent. White shapes represent the parts affected by emotional treatment.

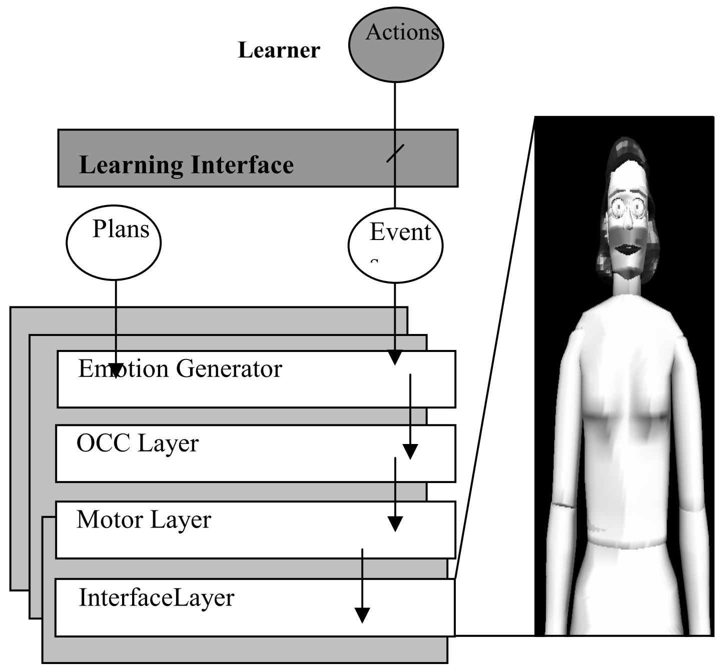


Fig. 2. The architecture of Emilie

Events are sent to the agent from the learning interface (virtual lab) model. These events are logical representations of specific user actions. Plans are, however, strings of events that are presumed to be the "right" procedure for the user to follow. The OCC Layer uses intervals and sign algebra to represent the state of the agent toward the emotional couples stated in the OCC Model at a given time using an expert system. The OCC Layer also has some aspects that are similar to those in Cathexis, such as the use of an extinction function. The Emotion Generator is in fact a set of relations on events, plans and records of past events that induce variations in the OCC Layer; these can be viewed as input relations. The motor layer, on the other hand, is a set of relations that defines how emotions expressed in the OCC Layer are translated into a representation in the agent's interface. The Interface Layer is a definition of the agent's appearance free of geometrical considerations. This definition is then used to produce a visual output of the agent.

This architecture has an advantage in that the information necessary for Emilie to produce emotional responses is very limited. The vision the agent has of its environment is a simple feed of actions from the user, expressed as degree of difficulty of the action accomplished (or to be accomplished in a case of failure) and the degree of student "wrongness", i.e. how far the student's action is from the expected action (the right action having a value of zero). The agent can also be fed a list of difficulty levels as a plan of the events expected by the user to succeed at his task of inferring emotions based on prospected events such as Fear and Hope.

A. What Data to Consider?

Since Intelligent Tutoring Systems tend to process very large quantities of information in various forms and on many different subjects, it is necessary to identify what should be considered when inferring emotions. While Gratch's [12] use of plans to generate emotions is clear and powerful, it seems inappropriate in the context of a coach such as the one envisioned in Emilie-1. The main reason is that, the agent cannot accomplish the path to its goal: in fact, the agent is essentially powerless. Also, while many problems presented in virtual environments can have solutions expressed in terms of plans, this is unlikely to happen for all environments, or merely introduces a limiting constraint on the activity's designer. We have identified a small number of facts that are of interest to our agent's role, limiting the use of domain-related knowledge while still allowing sufficiently believable feedback. Not all of the information tied to a user's action is relevant to the embodied agent. Domain-tied knowledge is nearly unusable for emotional purposes. The information we retained for all events arising from the user's actions comes down to two parameters: the degree of difficulty of the action accomplished (or to be accomplished in a case of failure) and the degree of student "wrongness", i.e. how far the student's action is from the expected action (the right action having a value of zero). Another parameter carried in an event but unused by the emotion generator layer is the one involving geometrical coordinates placing event occurrence on the screen. This parameter is used, however, by the motor layer to adjust the character's sight. Another type of event that is treated differently is the moment when the user undoes his last actions. This last category of action carries no parameters.

The plans received by the emotion generation layer consist of a list of the difficulty factors that should be encountered by the student before he completes an activity. This information is used to produce Hope, Fear, Satisfaction, Relief, Fears-confirmed and Disappointment.

B. Modulation of Emotion's Value Given the Context

While not specifically part of the agent responsible for emotion simulation, the system also uses a great deal of information from the user model. This information is used to adjust the difficulty level associated with an event so that it accurately reflects the difficulty the learner truly encounters. The user model contains information about the concepts mastered by the learner. In the curriculum we have prerequisites and concepts associated with an activity and, ideally, for each action corresponding to the steps required to perform the activity.

To determine the difficulty level associated with an activity or a step within this activity, we first retrieve an initial difficulty factor set by the designer of the activity. Arbitrary values or values obtained statistically about an activity's degree of difficulty are unlikely to reflect the difficulty encountered by any given learner. To come to a better evaluation, we make adjustments based on information available in the curriculum and in the user model. If a student masters all the associated concepts well beyond the degree required to perform the step or the activity, then we set the associated difficulty level to a lower value. If the episode (the context in which the degree of student mastery of a concept has been determined by the system) is judged to be similar to the current one, the difficulty level is set even lower because we consider that the user has already performed a similar task. If, however, the user displays borderline or even incomplete ability to succeed in the activity, the difficulty factor is raised to a higher value. Also, if the activity leads to a large number of new concepts, the degree of difficulty is set higher, because we assume that the activity involves a quantity of thinking and reasoning in order for the student to discover these new concepts. This adjustment to the difficulty level of an event is done before it is sent to the Emotion Generator (between the Virtual Lab Model and Emotion Generator layers).

The retrieval of a value to the parameter indicating how far the student is from the expected action is, of course, very domain related. There are, however, some guidelines that can be established. First, if the user is carrying out the expected action, the value should be zero. If the user is doing something unexpected, but that is not identified as a mistake, the value should be low. If the user makes a known mistake, then the value should be higher.

C. Generating Emotions

The Emotion Generator is a set of relations that defines how events, plans and past events should influence the variation of an agent's emotional state. Events are what trigger emotional variations, and these variations will be influenced by information from other sources. For example, a successful-action event creates a Happy-For feeling depending on how many mistakes the learner has made during previous attempts. Variations in this event are also influenced by how difficult the action is, compared to the actions previously encountered. Plans give an overview of how difficult upcoming actions will be. Plans are also used to influence how an action influences an agent's emotions. Using the same example, the emotions of Satisfaction or Relief are higher if this action was considered more difficult to accomplish than any of the actions still to come. These relations are expressed as "if-then" rules and are implemented in an expert system. This simplifies the task of specifying how different factors should influence an agent's emotional state with a low level of formalism (compared to mathematical functions). This is an example of rule that generate emotion:

```
(defrule soulagementPassageDifficile
   (reussite ?difficulte :(> ?difficulte *FACILE*))
   (erreurs (scope local) (nombre ?nbErr :(> ?nbErr 0))
   (bonnesActions (scope local)
                  (nombre ?nbsucces :(= ?nbSuccess 0)))
  =>  (changeEmotion Relief (* ?difficulte ?nbErr))
      (changeEmotion Fearr -(* ?difficulte ?nbErr))
)
```

D. Transforming Emotion's Value into Visual Feedback of the Embodied Agent

Once an emotional state is available for an agent, it provides new information about how that agent should interact with its world. Emotional information can be used to influence decisions, introduce variations in speech, music, color or many other as-yet-unknown applications. We have currently used emotional information to provide the user with a pictorial representation of the agent as a humanoid character.

When the emotional state of an agent changes, there are two ways in which the visual representation of the agent can be affected. In the first way, agent facial expression is inferred directly from its representation of emotions. Relations are specified between different emotions and facial characteristics. For example, a direct relation is established between the emotion of Joy and smiling, and inversely with Distress. In another example, the orientation of the head (see Fig. 3), main body and arms are slightly related to Pride.

The second way that changes in the OCC Layer can influence visual appearance is by initiating gestures. When changes in the emotional model exceed certain specified thresholds, they trigger small pre-recorded movements. For example, a sudden rise in the Sorry-For emotion triggers the gesture of the agent shaking its head, which is bent forward and looking down. A lower variation would have initiated a gesture of the agent briefly smiling downwards, lowering its outer eyebrows and slightly closing its eyes. These gestures amplify emotional feedback and increase representational power. They also make the transitions between different emotional states more obvious. This is an example of rule that that adjusts the embodied agent:

```
(defrule sourireDeBase
  (emotionChange Joy|Happy-for ?y )
  (emotion (higher Joy) (rate ?j )
  (emotion (higher Happy-For) (rate ?hf))
  =>
  (call ?*lecorps* setSourireDroit
      (max -100 (min 100 (+ ?j ?hf ?y))))
  (call ?*lecorps* setSourireGauche
      (max -100 (min 100 (+ ?j ?hf ?y))))
  (assert (bouche))
)
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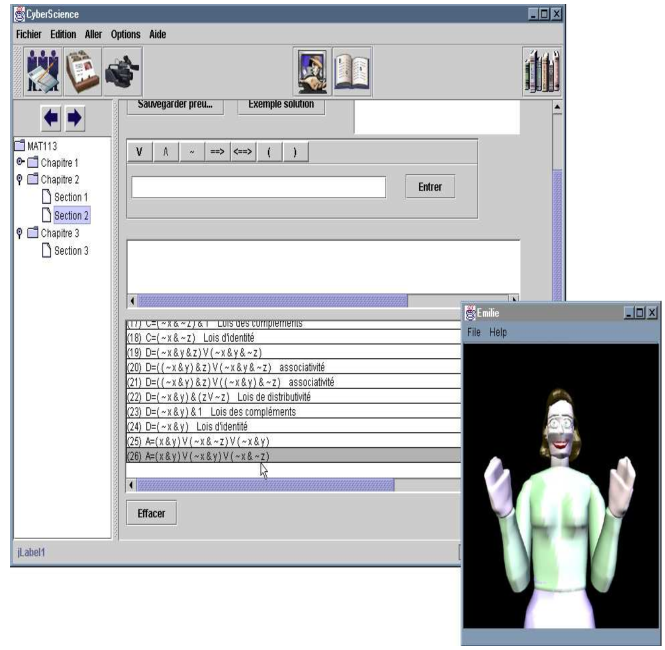


Fig. 3. The user has just completed a difficult activity

In Figure 3, the user has just performed an action that we know is a mistake by selecting the wrong item in the drop-down list. To show this, the agent looks at the source of the event with an expression arising from the sudden rise of disappointment and distress. Another example of a result is shown in Figure 3, where a sudden rise in relief, joy and admiration has created the visible expression. The facial expression is primarily due to Joy and Happy-for values, while the hand movement is a result of a strong variation in the Admiration and/or Relief levels.

IV. Emilie-2: An Agent for Emotion Recognition

A. Architecture of Emilie-2

Emilie-2 aims, via a digital camera placed over the screen, at carrying out the acquisition of face image and analyze the facial expressions, in order to identify the emotions. This agent is made of three layers (modules) (Fig. 4): the first one (perception layer) captures and extracts the facial expressions (image acquisition and face tracking) and proceeds to its categorization (classification); the second one (cognition layer) analyses and diagnoses the perceived learner's emotional state and the third one (action layer) takes decision on remedy pedagogical actions to carry out in response to the actual emotional state. Tutoring agents are then informed and may access information in the new affective state (updated by Emilie-2) to adapt the current tutoring flow accordingly.

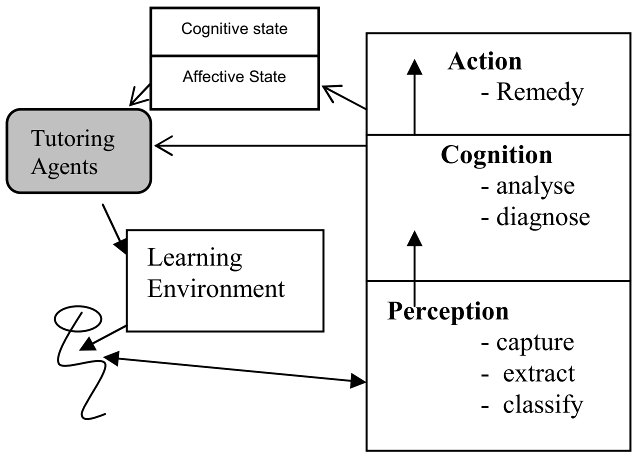


Fig. 4. Emilie-2 pedagogical cycle

The cognitive layer includes two main processes named analysis and diagnosis. The analysis of an emotional state recognized by the perception layer makes it possible to translate the meaning of this emotion in the learning context. It is carried out by taking into account several elements including the recognized emotion, the current affective profile, the historic of the actions realized before the emotion expression, the cognitive state of the student, the emotion evolution and the social context (if it corresponds to social or a collaborative learning). The emotion analysis may reveal if the student feels “satisfaction”, “confidence”, “surprise”, “confusion”, or “frustration”. These states are more precise in educational context and appropriated pedagogical actions can be taken in order to influence those emotions. Another important process in the cognition layer is the diagnosis of the analyzed emotional state. This process determines the possible causes which has led to this situation (success/failure in an exercise, difficulty of the tasks, lack of knowledge, incorrect command of the knowledge, etc.). This is done using the learner’s cognitive state and the historic of his actions.

The action layer of the architecture includes processes that take decision about relevant pedagogical actions which can control the observed emotional state, in order to place the student in a better state [14]. Diagnosis and remediation processes in Emilie-2 are similar to those already implemented in the profiler agent, because we suppose that the emotional reactions of the learner exclusively come from learning factors. In these conditions, our hypothesis is that, the expression of negative emotions can ‘only’ be justified in terms of cognitive problems (lack of knowledge, misconception, misunderstanding, mal-rules… Details on diagnosis and remediation processes in connection with cognitive problems can be found in [15]. In the next section, we present details of the perception layer.

B. The perception layer of Emilie-2

This layer aims at perceive and recognize the emotion expressed by the student, via the analysis of its facial expressions during learning session. The perception contains three steps: facial expressions extraction, reduction and classification. The next sections present our approach for the implementation of these functions in Emilie-2.

Facial expression extraction. In order to promote the agent’s autonomy, the facial expressions’ extraction consists in two successive tasks, the learner’s image acquisition, via a digital camera, and a face tracking, which both eliminate a lot of useless information, like the background.

Facial expression recognition. In order to realize the recognition, we use the connexionist approach. Indeed, we believe that the facial expression of an emotion cannot systematically be reduced to a set of geometrical characteristics, and that a more global approach, based on the whole face (or subparts of the face), should produce better results. Furthermore, a connexionnist system, following a learning process on pre-categorized patterns [16], should be able to proceed to a better generalization, allowing successful treatment on unknown pattern. Thereby, this module performs a recognition of facial expression, by classifying each image in one of the six basis facial expression categories defined by Paul Ekman [17] (we also use the neutral expression, as the 7th category). The recognition module consists of two sub-modules. The main sub-module is an artificial neural network which classifies each image in one of the seven facial expression categories. The second module which works upstream of the other, reduces the dimension of the inputs. Indeed, in order to generalize the classification, an artificial neural net might use dimensional reduced inputs. A face image, even without background, still contains too much information (256 per 256 pixels represents 65536 inputs), which make it difficult to generalize.

Data reduction module. Among the different existing methods [18, 19, 20], we have decided to use the decomposition by Eigenfaces [19, 21, 22], a method which is well documented, simple to implement, and which may lead to good recognition results (79.3% according to [18]). This method is based on the fact that there is a correlation between different pixels in an image, which means that, it is possible to come out with reduced information that can characterize the whole image. By extracting the relevant information, this method constructs a sub-space which clearly shows the significant variations of the picture, and we reduce the initial images by projecting them into this sub-space. Thus, this method constructs a new base on the eigenvectors of the images covariance matrix, and expresses each image as a linear combination of these vectors (called “eigenfaces”) (Fig. 5). We obtain a reduction of the size of the images, because the linear coefficients are sufficient to characterize the image. Once the calculus of the eigenfaces has been made, this method selects the most relevant, those who are associated to the highest eigenvalues.

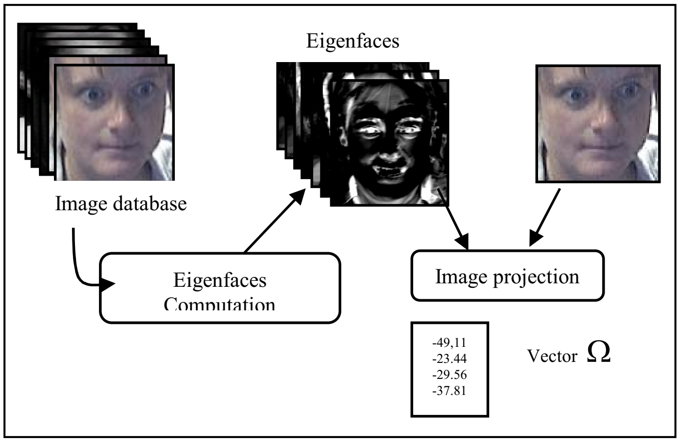


Fig. 5. Description of the eigenfaces reduction method

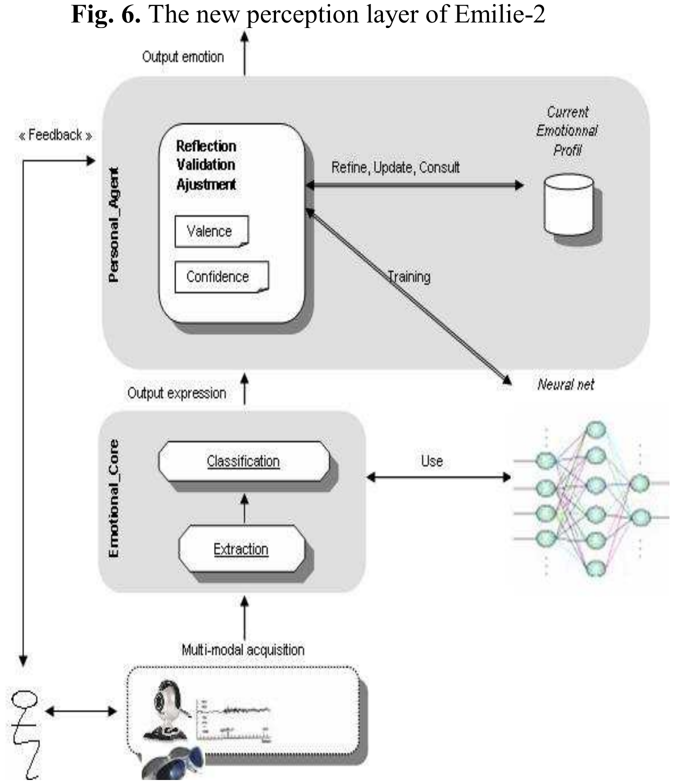
Facial expression classification module. Once the extraction of the relevant information has been made, the facial expression recognition is processed using an artificial neural network. Its architecture is made of three layers: an input layer, which provides the images, and is composed of a number of neurons corresponding to the result of the data reduction process, one hidden layer, for which we will search the adequate number of neurons, and an output layer composed by 7 neurons, one for each basis facial expression plus one for the neutral expression.

C. Results

Given the results we obtained, there are too much problems with the proposed perception component: 1) Face detection using Eigenface method is too much limited and less accurate. The approach is very sensitive to some variations (head position, color...). As these variations are inevitable in learning context, this method becomes very difficult to work in this context. Although we proposed some solutions to overcome variations, it appears that, pre-processing tasks hide some errors that are propagated to the overall perception processes. 2) The facial expression extraction mainly relied on variation of the face. Hence, two identical faces with a position variation of the order of 5 pixels will lead to two different eigenvectors and thus, may be interpreted differently during the classification. 3) The perceptron neural net used is very sensitive to the entry variations and doesn't take into account the variation problem states previously for the 500 eigenvectors that are used in the ideal configuration. Also, the network size is very high given that the number of weights is around 35000 and the value of the acceptable error is 0.01. Thus, up to 3500000 images (what is too much!) are needed for a good training of that network. 4) The current version of the perception component doesn't take into account the emotion valence which is very important in our application.

Given the problems stated previously regarding the current implementation of Emile-2's perception layer, we developed a new version using feature-based approach for face detection. The approach allows to search for different facial features (eyes, nose, mouth…) and to extract their spatial relationships which are used to compute distance variations (given a reference neutral expression). Thus a vector of those differences is given as input to the neural net. We extend the initial architecture by introducing a new component called 'personal agent' (Fig. 6) which makes it possible the adaptation of the neural net training to a specific user. The neural net is a perceptron with 8 entries corresponding to the 8 most important distance variations that have been retained. The network also consider emotional valence with 3 possible values (small, medium, high) for each of the 6 emotions. That means 18 outputs + 1 (for the neutral expression) and 14 hidden layers. If we limit ourselves to 3 relevant emotions for learning context, we will have a network of 8 entries, 10 outputs and 10 hidden layers. The *Emotional_core* is actually implemented using MPT (The Machine Perception Toolbox) developed by the university of California, San Diego. The neural network is configured but should be trained with relevant databases containing normalized faces.

Fig. 6. The new perception layer of Emilie-2



V. Conclusion

Intelligent Tutoring System must enrich student-tutor interactions with more personalized communications (explicit and/or implicit) based either on cognitive and affective behaviour. This provides flexible tutoring process during learning process, context-sensitive help and explanation. We proposed a multi-agent system with agents that manage both cognitive and affective model of the student and that are able to express emotions through embodied agents.

Emilie-1 is an agent core in charge of tutor's emotion state management. It determines the emotion to be expressed by analysing the learning trace and considering the student current performance. Emilie-1 can be integrated in any tutoring agent (coaching agent, critiquing agent…).

Emilie-2 is in charge of learner emotion detection. It establishes the learner emotional state by capturing emotions he or she expressed during learning activities, and draws some conclusion concerning the possible cause of those emotions. This provides a basis for learning process adaptation.

Emilie-2 currently capture emotions only through facial expression analysis but we are working on a multimodal version of the agent that will be able to integrate information from different sources including vocal information, physiological channels such as pressure, and posture.

We hope that tutors built on this architecture will contribute to raise the student's productivity by involving him in a constructive interaction to reveal aspects of his learning states (both cognitive and emotional). In fact, Agents endowed with affective anticipation and planning capacity may optimize the learner behaviour, facilitate their enjoyment of the learning situation. Providing consistent empathy using body language, animated pedagogical emotional agents could be able to induce, influence a particular mood state to the learner (emotional contagion) [23], or at least a positive impression [24].

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