CalliSmart: an Adaptive Informed Environment for Intelligent Calligraphy Training

Rémy Frenoy[*], Indira Thouvenin[*], Yann Soullard[*], Olivier Gapenne[†]

[*]Sorbonne University, Université de technologie de Compiègne, CNRS UMR 7253 Heudiasyc

CS 60 319 - 60 203 Compiègne cedex

[†]Sorbonne University, Université de technologie de Compiègne, CNRS UMR 7338 Biomechanics and Bioengineering

CS 60 319 - 60 203 Compiègne cedex

Emails: {remy.frenoy — indira.thouvenin — yann.soullard — olivier.gapenne}@utc.fr

Abstract—Gesture learning is a complex and multistep process where trainees are supposed to improve several psychomotor and cognitive skills. According to numerous studies, trainees need to be provided with various types of feedback to improve these skills. These studies also highlight that benefits of a given type of feedback depend on trainees situation. Therefore, feedback must be chosen according to an analysis of trainees activity. Sensorimotor approaches have investigated the impact of feedback on specific learning situations, but the analysis of gestural activity, which would allow the automatic selection of an appropriate type of feedback, is still a recurring issue. In this paper, we propose a new model for gestural training systems based on smart interaction. This model relies on a recognition module based on Naive Bayes classifiers, representing trainees activity by a vector describing their errors, and representing training environments by vectors describing their set of implemented types of feedback. We present a platform for calligraphy training we designed and developed based on our model. Through a user study, we emphasize the benefits of our approach on trainees development.

Keywords–Training Systems, Interactive systems, Adaptive Systems, Gesture Recognition.

I. INTRODUCTION

Gestural training systems have been studied in various research fields, which can be divided into two families: sensorimotor approaches and modeling approaches. Sensorimotor approaches focus on the impact of providing a specific type of feedback on trainees activity. Virtual training environments belong to these approaches, and enhance training by providing real-time 3D feedback. Such systems have been used for different kinds of gestures, such as welding gestures [1], obstetric gestures [2], or pottery gestures [3]. Haptic systems are also part of sensorimotor approaches, as they investigate trainees kinesthetic memory [4] by adding proprioceptive cues during visuo-motor learning tasks [5]. These systems have proven to benefit motor skill training, including within the context of handwriting [6]. Although these fields focus on the impact of providing a specific type of feedback in a given context, they do not question the issue of modeling gestural activity, nor the issue of adapting feedback according to this model. Yet results have shown the benefits of providing diversified [7] and personalized [8] feedback on the learning experience.

Intelligent tutoring systems are part of modeling approaches. A key feature of these systems is the adaptation of learning content and difficulty level to the trainee. This adaptation requires an accurate student model [9] which allows for individualization [10]. These systems process interpretable data (results from a form, answer to a multiple-choice question). Such systems do not capture motor skills, which necessitates the use of sensors and results in huge amount of data which need to be processed to become interpretable. Furthermore, although intelligent tutoring systems model students knowledge, very few studies have tackled the issue of modeling gestural activity.

Calligraphy training is an interesting case study. When trainees learn calligraphy with a human teacher, the teacher analyzes trainees gestural and cognitive activity. The teacher also analyzes trainees drawing to identify patterns of error. From this analysis, the teacher can provide various guidance by giving verbal advice and focusing trainees attention on specific characteristics, or demonstrating the gestures. With such training, trainees build a knowledge based on their experience and the kinesthetic memory of the gestures, leading them to the acquisition of control and regularity, which are essential skills to produce calligraphy. We believe that being able to model users activity from sensor data, so that systems adapt according to this model, would enhance trainees gestural learning experience. Therefore, our goal is to model and link highly variable sensor data representing trainees performances over training time, and training environments containing their set of implemented types of feedback.

This paper proposes CalliSmart, an intelligent interactive system with gestural input, relying on a framework which makes it possible to place trainees in a representation space, from which it is possible to analyze the evolution of their performances. By placing feedback types in this representation space depending on their relevance in a given situation, the system provides appropriate types of feedback to trainees according to their activity. The paper is structured as follows: the next section present an overview of related studies. Section III introduces our interaction model. Experiments are presented in Section IV, and results are exhibited in Section V. Finally, we discuss these results and introduce future works in Section VI.

II. RELATED WORK

This section introduces several studies investigating the process of gesture learning, and the impact of feedback on this process. As these studies advocate to provide a diversity of feedback, research works on learning modeling and gesture recognition are then presented.

A. Gesture learning

Trainees learn gestures through different steps, each step involving cognitive, psychomotor or biophysical skills [4], [11]. In each of these steps, trainees build very specific gestural and kinesthetic abilities, and focus on very different parts of their activity (Figure 1).
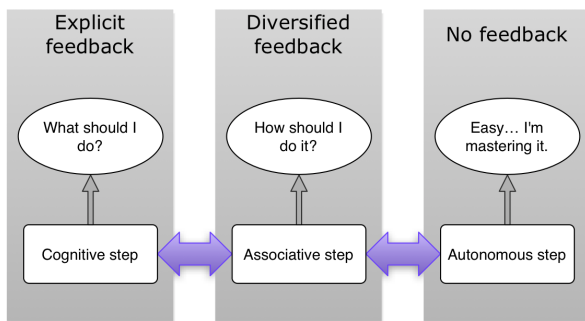
Figure 1. The three steps of motor skill learning, inspired from [11].

Although some questions still have to be answered, most learning strategies advocate to give very simple and precise information to trainees in the cognitive step, trainees in this early stage of learning being very prone to suffer from cognitive overload. In the associative step, trainees need very specific feedback to understand their errors and correct them. They can also benefit from knowledge of performance feedback (KP feedback). Finally, in the autonomous step, trainees barely need feedback, but can benefit from knowledge of results feedback (KR feedback). Hence, it is the variety of (appropriate) types of feedback which helps trainees during their learning process by enhancing their perception of their performance. This variety is also essential to avoid the syndrome of *dependence to the teacher* [12], where trainees improve their performances on a training system but are unable to transfer these improvements in a real environment.

B. Intelligent tutoring systems

Providing a variety of feedback types is a concern tackled by Intelligent tutoring systems (ITS). ITS aim at modeling the students activity by collecting knowledge about them. Knowledge represented in these models can include students skills, affect, experience, or stereotypes [13]. From these models, ITS can analyze how trainees develop over time, and use this knowledge to determine the most efficient training situation. To build and update these models, ITS use cognitive techniques (model-tracing, constraint-based), or artificial intelligence techniques (formal logic, expert-systems, planning, Bayesian belief networks). From a student representation, ITS can provide various types of feedback by following a learning strategy. The main learning strategies either follow the *behaviorist* approach, which considers learning as a set of modifications directly correlated with trainees actions within the learning environment; the *cognitive* approach, which claims that unobservable and internal constructs (perception, motivation) influence the learning process; or the *constructivist* approach, which holds that individuals construct the world in their own way, implicating that training should be focused on the student activity more than on training monolithic strategies.

ITS acquire interpretable data: a score from a test, an answer to a multiple choice quiz. Thus, ITS cannot deal with sensor data, as they are not explicit enough to be used directly. Modeling gestural activity in the same fashion ITS model students knowledge necessitates a recognition process to make gestural data acquired from sensors interpretable.

C. Recognition

Research in gesture recognition has been growing to look for the best way to make sense of sensor data. The most popular approaches [14] either rely on matching-based strategies (Dynamic Time Warping, k-Nearest Neighbors), which compute a distance between the data to label and labeled data from a training database; or on learning models (Markovian models, Support Vector Machines, Naive Bayes Classifiers), which are optimized to model or discriminate training examples from different classes. Such methods have numerous applications, from intelligent training [15], to gestural training [3], or human-robot collaboration on assembly lines [16]. A recurrent issue when dealing with the recognition of gestural or cognitive activity is the issue of multilabeling, when a data sample can be labeled not only with one label, but possibly with a set of labels [17]. The existing methods for multilabel classification can be divided into two main categories: the *problem transformation* methods, which transform a multilabel classification problem into one or more single-label classification problem, and the *algorithm adaptation* methods, which extend specific learning algorithms to directly handle multilabel data [18]. Within the context of gestural training, multilabel recognition makes it possible to detect several patterns of error at once, and hence to consider every aspects of trainees performance when determining which types of feedback to provide.

D. Feedback

Numerous research projects have investigated the impact of feedback which should, no matter whether it is delivered by a teacher or a computer, "enhance learning, performance, or both, engendering the formation of accurate, targeted conceptualizations and skills" [19]. With the possibilities brought by the emergence of tablets and haptic devices, feedback has been studied through its sensory modalities (visual, audio, visuo-haptic), certain modalities being more appropriate than others depending on the context [20]. Temporal features (static or dynamic feedback, temporal information) are also determinant, studies showing that changing feedback temporal features make trainees develop different components of their gestures [21]. If some configurations have proven to be more or less effective than others depending on the training situation, it appears that each configuration has its advantages and drawbacks, depending upon the learning situation and trainees abilities [19], [22].

III. INTERACTION MODELING

Providing a variety of appropriate feedback types throughout the learning enhance trainees learning [22]. A fundamental issue when creating a gesture training system is therefore to decide which type of feedback to provide in order to maximize the benefits for trainees learning. This issue can be split into four issues: 1) The recognition and modeling of gestural and cognitive activity. 2) The definition of a set of feedback types the system can provide. 3)The selection of the type of feedback to provide depending upon the situation. 4) The evaluation of trainees learning throughout the training process.

To tackle these issues, the activity first have to be captured. Then, the acquired data must be recognized and a representation model of trainees learning state must be built. Finally, various types of feedback have to be designed and implemented. Depending on the modeled learning state, a

subset of feedback types is selected. This subset must be well-chosen (appropriate according to trainees learning state) to make them improve their skills (Figure 2).
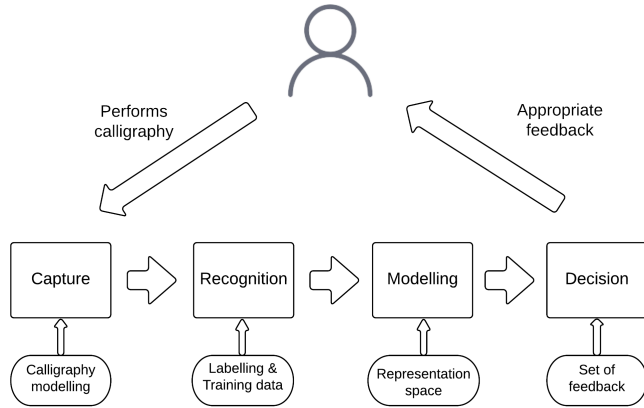

Figure 2. The CalliSmart process for smart Human-Computer gestural interaction, within the context of calligraphy training.

A. Capturing calligraphy features

Van Galen [23] defines handwriting as a "multi-component task implying cognitive, psycho-motor and biophysical processes". Handwriting is a motor gesture, where performers constantly analyze and modify their movements from their perception of their current actions, and their internal representation of the "ideal" actions. Furthermore, writers not only react to their actions, but also have a spatial and temporal representation of the shape they intend to draw. These representations imply a principle of anticipation, which means that performers have, besides modifying in real-time their movements according to their perception, to anticipate their future movements. Thus, learning handwriting necessitates having a cognitive representation of the shape to draw, and a perception of the different steps necessary in order to construct this shape (acceleration, angle, curve). It is also essential to spatially visualize the location of the current drawn shape, by comparison with locations of the previous shapes and the next ones which will be drawn (principle of anticipation, Figure 3).

In calligraphy, the goal is to analyze trainees performances according to two main criteria, which are the regularity and the visuo-spatial attention. Relying on these criteria, we propose to analyze trainees activity from identified types of errors. For each of them, we compute the probability of having the type of error given the trainee's performance. Trainees performance can be modeled by the vector $\vec{U} = \{x_1, x_2, x_3, , x_n\}$ where n is the number of patterns, and x_i corresponds to the probability of having the pattern i. Each pattern being a pattern of error, $\vec{U} = \vec{0}$ refers to an expert, and $\vec{U} = \{1, 1, 1, , 1\}$ refers to an absolute novice.

B. Interaction modeling

Three phases of interaction can be distinguished from the process illustrated in Figure 2:

- The trainee performing on the system. (A)
- The system providing feedback to the trainee. (B)

- The trainee making changes/adjustments throughout the process of interaction. (C)

We propose a space of representation S which aims at representing these processes. First, (A) is modeled by the vector $\vec{U}$ as previously explained. Each type of feedback implemented in the system is represented in S by a vector $\vec{F} = \{y_1, y_2, y_3, , y_n\}$, where n is the number of error criteria and y_i is the level of the ith error criteria for which feedback type F is the most relevant. Hence, F is considered optimal in the situation $\vec{U} = \vec{F}$ (B). Each coordinate of $\vec{F}$ is empirical and come from an expertise: the expert studies each type of feedback and decide in which situation it should be provided. Changes in trainees activity (C) can be tracked through transition vectors $\vec{Tr}_i = \vec{U}_i - \vec{U}_{i-j}, 1 \le j \le i \le n$, n being the number of recorded performances for the studied trainee.

C. Decision

In our approach, $\vec{U}$ represents the performance of a trainee, and each vector $\vec{F}_i$ represents an element in the set F of implemented feedback types. According to the representation, the most appropriate feedback type is the one represented by the closest vector to the current position of the user. Let $\vec{F}_a$ be the most appropriate type of feedback in the situation $\vec{U}_t$,

$$\vec{F}_a = \operatorname*{argmin}_{\vec{F}_i \in \mathcal{F}}(||\vec{U}_t - \vec{F}_i||_p) \qquad (1)$$

IV. EXPERIMENTS

By analyzing trainees performances throughout several exercises, it is possible to investigate the influence of providing various types of feedback on the evolution of their performances, and hence on their progression. Experiments should determine whether 1) providing feedback will improve the learning process, and whether 2) providing feedback will reduce the variance between performances by enforcing trainees attention on the task.

Within the process of calligraphy learning, a famous exercise is the "minimum" exercise (Figure 3). It is used to train regularity and visuo-spatial attention by asking trainees to repeat a similar pattern. On a perfectly executed exercise, white spaces between elements should have the same area, and elements should have the same shape in term of slope and size.
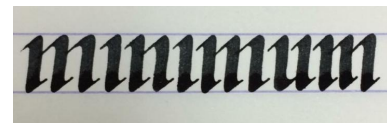

Figure 3. The "minimum" exercise in calligraphy.

The experiment focuses on the strait vertical lines of the minimum exercise. Participants are asked to produce a series of straight lines using a Wacom Cintiq tablet (Figure 4), with the same obligations than in the minimum exercise: spaces between lines should be regular, lines should be straight and vertical. Staves are displayed to limit the calligraphy area. This exercise exhibits the main features constituting the cognitive and psycho-motor processes surrounding calligraphy and the drawing of the "minimum" word.
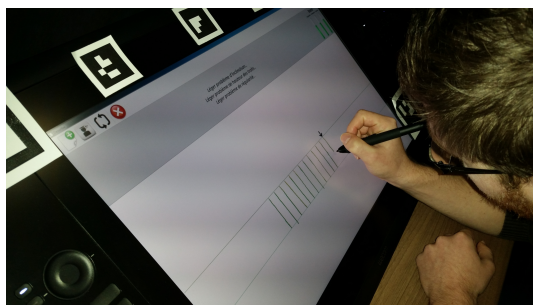
Figure 4. The CalliSmart platform.

A. Recognition

A database was created to train the recognition module. 46 participants were involved in the creation of the database. They had none to very little experience using a graphic table or practicing calligraphy. Each participant was asked to perform a series of three exercises, an exercise being a sequence of 10 to 15 strokes. Experts classified and labeled these exercises by examining both the gestures (participants were video recorded) and the results (screenshots were taken at the end of each exercise). Labels identify three patterns of error: slope error, size error, and regularity errors (irregular spaces between strokes). Several errors potentially appearing on a single exercise, the recognition of an exercise is a multilabel problem. The acquired database contains 138 examples labeled by two experts. Examples are unequally distributed among error classes, as some patterns appeared more often than others. The training database has been built using a subset of the 138 acquired examples, making balanced the number of error patterns. The final training database uses 40 examples per error pattern. Recognition relies on four Naive Bayes classifiers, one per class which are trained on examples from the training database (one-vs.-rest strategy). A 5-fold cross-validation was performed on the dataset. Classifiers used the features described in Table I as a representation of an exercise. Table II shows the recognition results, using classic multilabel evaluation metrics [17]. As stated in [17], the subset accuracy metric tends to drop fast when the number of labels grow, or when the amount of data is small. In our context, finding the exact combination of label is important, but not essential. The most important feature of the recognition process is its ability to recognize correct labels (errors trainees actually made). Improving these results will be one of our challenges in the future. An increase in the amount of training data and the use of a discriminative model may lead to an improvement of the results.

B. User study

1) Participants: A total of 28 people participated in the study. Participants were people working at the university, students in computer science, design and mechanics, with no to very little expertise in calligraphy. They were randomly and evenly distributed into the two experiment conditions described below.

2) Experimental procedure: The first group *(no feedback group)* did not receive any feedback. The second group *(feedback group)* received feedback from the following set of implemented types of feedback: 1) Real-time feedback

assists trainees by making them focus on a specific category. "Regularity" feedback displays where trainees should begin their next stroke (Figure 5a); "slope" feedback colors the stroke with a color from green to red depending on the slope (Figure 5b); "size" feedback highlights with a different color the limits of the drawing space (Figure 5c). Trainees can be assisted with every combination of feedback types, depending on the recognition of their activity. 2) Knowledge of results feedback (Figure 6), indicates the level of the trainee in each category ("r", "v", "l"). KR feedback is always displayed.
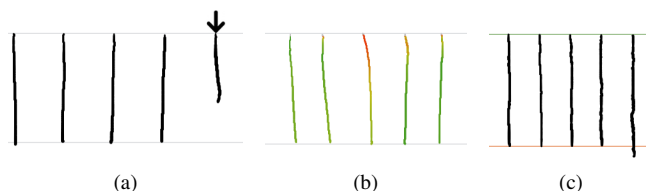

(a)   (b)   (c)

Figure 5. Real-time feedback aiming at assisting trainees with regularity, size, or slope error.
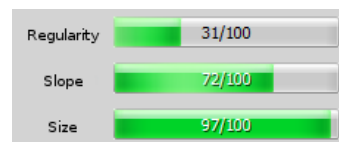

Figure 6. KR feedback providing trainees with explicit indications regarding their performance.

Feedback was chosen depending on trainees activity during a whole exercise. Hence, feedback depends on the previous exercise and cannot change until the end of the current exercise. Each participant was asked to perform a series of six exercises, an exercise being itself a series of 10 to 15 lines to draw. The first series was not saved and allowed trainees to familiarize with the platform. For the feedback group, the system used this first series to decide which feedback types to provide during the first recorded series. Our hypothesis are:

- **H1** Participants in the feedback group will improve better than participants in the no feedback group.
- **H2** Variance between participants will be lower in the feedback group than in the no feedback group.

At the end of the fifth series, we asked participants to perform a last series. This series was performed without any feedback from the system for the two groups, to compare their performances in the same conditions. This last experiment should test our third hypothesis:

- **H3** Participants in the feedback group will outperform participants in the no feedback group in real conditions.

V. RESULTS

To evaluate participants performances, a dataset of expert performances was created, gathering 22 exercises performed by three different people. The same representation was used in the recognition and in the evaluation processes, participants as well as experts being represented by their feature vectors (Table I). In a similar way of a k-Nearest Neighbors algorithm,

TABLE I. Features computed from trainees activity.

Slope error	Angle of the most sloping stroke, using real stroke coordinates.
	Angle of the most sloping stroke, using linear regressions of strokes.
Regularity error	$\frac{\max(distance)}{\min(distance)}$, using distances between consecutive strokes.
	$\frac{\max(area)}{\min(area)}$, using areas between linear regressions of strokes.
	$\frac{(\max(area) - \min(area))}{\mu(area)}$, using areas between linear regressions of strokes.
Size error	Maximum difference between stroke vertical size and stave size

TABLE II. Validation results of the recognition process on multilabel data.

Recall	Precision	Hamming Loss	Subset Accuracy	Accuracy
0.79	0.83	0.70	0.55	0.72

we evaluate our method by computing the Euclidean distance between a trainee performance and its k-closest expert representations. Such a method reduces potential bias induced by a parametric modeling. In our experiment, the value k is empirically set to three. We carried a Shapiro-Wilk test on the result data, which showed that data were not normally distributed. Therefore, we performed the non-parametric Mann-Whitney test to confirm the efficiency of our method.
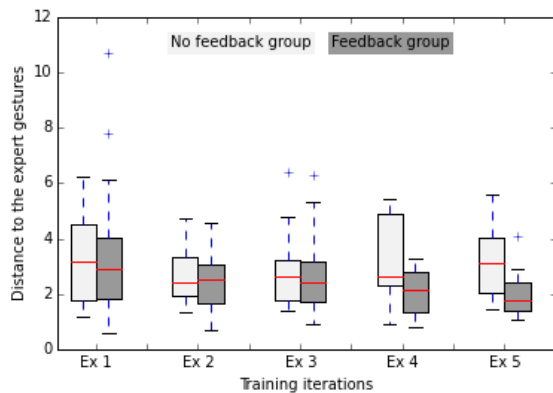

Figure 7. Distance between trainees and expert performances over the training iterations.

Figure 7 illustrates a significant improvement of performances for the feedback group, from a distance of 2.88 at the end of the first exercise, to 1.75 at the end of the fifth exercise, while the no feedback group only slightly improved, from a distance of 3.20 to 3.11. A two-tailed Mann-Whitney test was performed between the two groups for the fifth exercise, which resulted in a p-value of 0.029. We can hence confirm our first hypothesis (**H1**), which is significant at a standard 0.05 threshold. Variance between participants in the feedback group drops over the training, which implies a convergence of trainees performances (Figure 7). Variance between participants in the no feedback group stays high over the exercises. These two observations confirm our second hypothesis (**H2**). Results obtained in the no feedback group can be explained by two factors: incomprehension and weariness. The task proposed in this experiment is repetitive, and participants

in the no feedback group did not see any changes in the training environment throughout the exercises. From the fourth exercise, they seem to suffer from a loss of focus as they do not see any improvement or changes that would reflect their performances. Participants often asked how well they were performing, indicating that they were seeking for information reflecting their performances. People in the feedback group could see their improvement through the KR feedback at the end of each exercise. Moreover, a real-time feedback tailored to the errors made in the previous exercise was provided, helping them understand their performance, and improve on the aspects they needed the most. Figure 8 illustrates the results of the last exercise with participants form each groups performing in real conditions, without feedback. We note that participants from the feedback group outperform participants from the no feedback group. Moreover, performances of the participants in the feedback group only decrease from a distance of 1,75 to the expert to a distance of 1,88 between the fifth exercise (with feedback) and the sixth exercise (in real conditions). This result is promising, since the *dependence to the teacher* syndrome tends to make performances drop significantly when trainees trained on aided system first perform in real conditions. However, variance between performances in the feedback group in the sixth exercise grows compared to variance measured in the fifth exercise. This grow in the variance is reflected by the Mann-Whitney test, which results for this last exercise in a p-value of 0.05486. Differences between our two groups on this last exercise is hence significant at a 0.1 threshold, but not at a 0.05 threshold. Further experiments should thus be conducted to fully confirm our third hypothesis (**H3**).
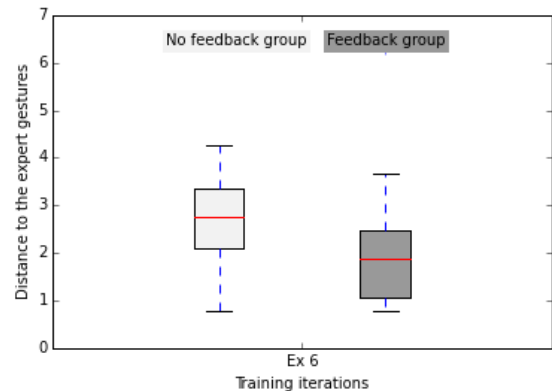

Figure 8. In real conditions (without any feedback), performances of participants trained with, and without feedback.

VI. DISCUSSION AND CONCLUSION

In this paper, we proposed a new model for gestural training systems based on smart interaction. In opposition to intelligent tutoring systems input data, our input data come from sensors and are not directly interpretable. Our system relies on a recognition module based on Naive Bayes classifiers, which aim at recognizing pattern of errors in trainees activity. This module provides probabilistic outputs, one per pattern of errors, that we use to build a representation of trainees activity in n dimensions, n being the number of possible errors. This representation is used to determine the types of feedback to provide to the trainee.

An experiment comparing the progression of two groups, one with feedback and one without feedback, showed that trainees perform better when provided with appropriate feedback, compared with trainees trained by practicing in real conditions. Variance between trainees performances was also reduced when they were provided with feedback. A last experiment, where participants in the feedback group had to perform in real conditions, showed that they still outperform trainees from the no feedback group, and that their performances only slightly drop from training to real conditions. These last results should be confirmed by further experiment, but seemed to highlight the benefits of our system to reduce the effects of dependence to the teacher.

In future works, we will extend our recognition system so that it should be able to detect a larger number of errors, and thus have a more precise recognition of the gestures. More types of feedback should be implemented so that the system can choose the appropriate configuration in a larger number of possible situations. An interesting issue regarding feedback is how well it is adapted to a situation, and to a trainee. In intelligent tutoring systems, the pertinence of a specific feedback type is determined empirically or from study results. One could argue that users have their own sensitivity and comprehension (cognitive and constructivist approaches, see Part II-B), and that systems should be able to reconsider, as experienced human tutors do, what they thought to be an appropriate type of feedback. We will investigate this issue, and examine the possibility of adding another degree of adaptation in our interactive gestural training system. We will also evaluate the impact of this adaptation on trainees learning experience.

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