Augmentation of practice with expert performance data: Presenting a calligraphy use case.

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Abstract

After the first two years of experience performing a job, any extra experience time has frequently been found to have little to no influence in performance of the job. Only individuals that indulge in deliberate practice achieve the superior performance. The mentors are crucial for deliberate practice because apprentices does not engage in deliberate practice spontaneously. However, experts typically have more knowledge than they can verbalize, which impedes their capability as a trainer. In addition, there are not enough experts to closely train apprentices to foster deliberate practice. We argue that augmented reality and sensors along with a proper methodological approach may help in mitigating these problems. To exemplify our argument, we developed the calligraphy application, which records calligraphy experts to provide guidance and feedback on the current performance of the apprentice for supporting deliberate practice. This application was built using a Microsoft Surface, Hololens and Myoband™. We also present our framework for using sensors and augmented reality in the context of capturing and utilizing expert performance data.

Introduction

Two apprentices practicing their skills for the same duration can result in significantly different level of gains. Simply practicing a skill repeatedly does not account for superior performance (Ericsson, Charness, Feltovich, & Hoffman, 2006). To achieve this, practice should be deliberate i.e., aimed at improvement of particular skill by reflecting on previous performance (Ericsson et al., 2006). However, an apprentice does not engage in deliberate practice spontaneously (Ericsson, Prietula, & Cokely, 2007). It is difficult to perform or maintain deliberate practice because it is cognitively demanding for the apprentice to be conscious of his/her own performance (Rikers, Van Gerven, & Schmidt, 2004). Therefore, expert mentors are crucial to support deliberate practice in apprentices (Ericsson et al., 2007). Deliberate practice requires one-to-one settings where an expert continuously provides guidance and feedback to the apprentice (Carey, 2014). Unfortunately, experts cannot always be there to provide feedback on the apprentice’s practice at all times which may impede his/her deliberate practice. In addition, experts also tend to underestimate how difficult a task can be for apprentices (Hinds, 1999). Learning from experts is difficult because an expert typically has more knowledge than he/she can verbalize (Patterson, Pierce, Bell, & Klein, 2010). Experts are also often unaware of all the knowledge behind their superior performance and thus, omit information that apprentices may find valuable (Patterson et al., 2010). Modern sensor based technology can capture rich representation of expert performance, which can be reused to provide continuous feedback to the apprentice, supporting deliberate practice. Therefore, we argue that sensors and AR can assist apprentices in practicing deliberately by providing expert based feedback.

A sensor is commonly defined as: “a device that detects or measures a physical property and records, indicates, or otherwise responds to it.” (“Definition of sensors by Oxford Dictionaries,” 2018). Capturing the expert performance with sensors opens many possibilities to train apprentices based on expert data. For example, captured information sometimes may even be invisible to apprentices but crucial to the task. Sensors have the capability to unobtrusively measure observable properties, which are ideal for capturing “expert performance”. Sensors have already been successfully used to train apprentices based on expert performance data (e.g. Jarodzka, Van Gog, Dorr, Scheiter, & Gerjets, 2013; Schneider, Börner, van Rosmalen, & Specht, 2017). Bower & Sturman (2015) have also elaborated on the educational affordances of sensors and Augmented Reality (AR) and their potentials for training in authentic contexts.

AR provides a rich multimodal and multisensory medium for the apprentice to observe the captured expert performance. A key aspect of AR is to overlay the real world with virtual content to create an immersive platform (Bacca, Baldiris, Fabregat, Graf, & Kinshuk, 2014) which places the apprentice in an authentic context engaging all his/her senses. By AR, we do not confine ourselves into the augmented display category but rather broad spectrum of augmentation of senses with other sensors and feedback devices. Modern AR systems can also communicate with various sensors in real-time, which can offer broad range of training affordances. These affordances of AR and sensors posit many potentials to train apprentice by using the captured expert performance which allows apprentices to receive the expert's guidance and feedback during training (Guest et al., 2017).

To support apprentices attain deliberate practice by means of expert based feedback and guidance, the paper outlines a theoretical approach of using sensors and AR. In addition, the proposed calligraphy tutor system described in this paper implements this particular model. This paper describes the proposed solution in the form of prototype in the followings. It closes with discussions and future work to be performed.

Theoretical Framework

While sensors and AR posit a rich educational potential for training, Bower & Sturman, (2015) have also stressed the issue of putting technology before pedagogy. This is especially true for emerging technologies such as sensors and AR which provide affordances potentially beneficial for training and education. Therefore, to ensure we are guided by proper pedagogy, the proposed framework is structured around the pedagogical framework known as Four Components Instructional Design (4C/ID) model. The 4C/ID model supports training of complex skills and has close resemblance with underlying principles of deliberate practice (Neelen & Kirschner, 2016). Sarfo & Elen (2006) assessed educational systems developed with 4C/ID specifications and positively indicated that the 4C/ID model promoted the deliberate practice. Evidence about the effectiveness of training environments designed in line with specifications of the 4C/ID model for the promoting deliberate practice in training contexts has also been documented by Van Merriënboer & Paas (2003) and Merrill (2002).

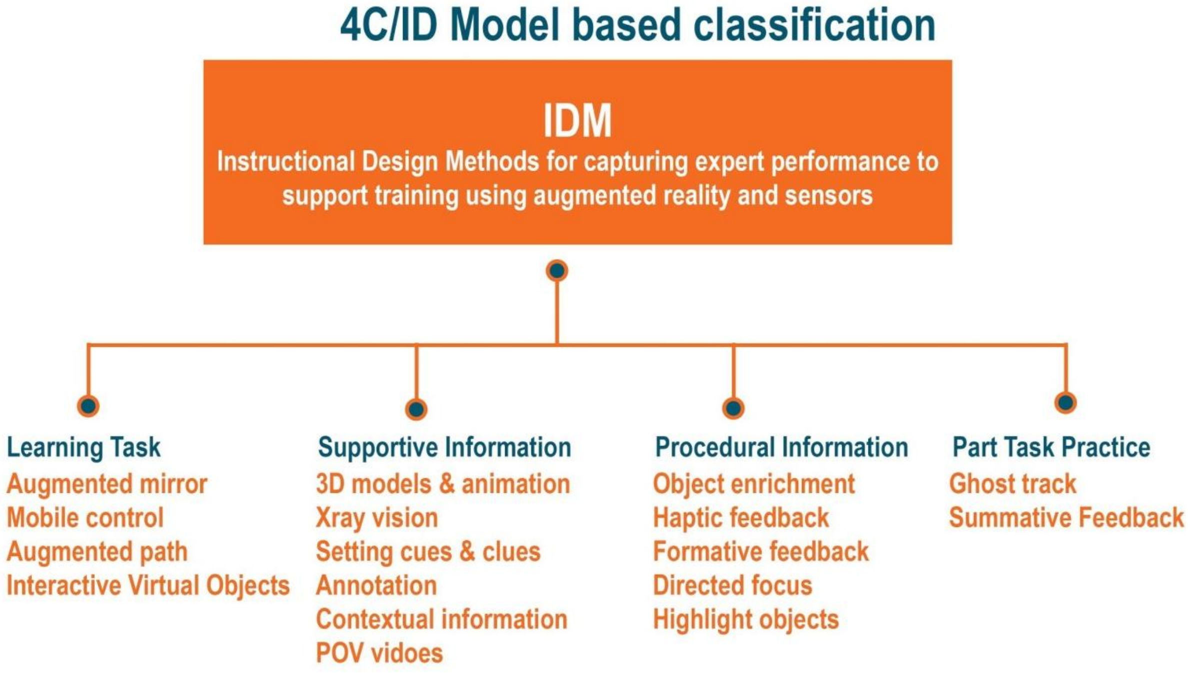

Figure 1: Categorized Instructional design methods under the four components of 4C/ID model.

Table 1: General Instructional Design Methods characteristics

Description How can the features be described? What skills are being addressed?	
Requirements for Capture What types of sensors are required? What type of data must be captured?	**Requirements for Enactment** What sensor is required for enactment? What type of data is required enactment? How is this feature enabled by/for the apprentice? Which interaction means does the apprentice have?

The 4C/ID model is a non-linear and systematic processing model for designing a complex learning environment. The basic assumption of the 4C/ID model is that all complex learning can be represented in combination of four components described by the model (Van Merriënboer & Kester, 2014) (see Figure 1). To complement the 4C/ID model with the affordances of sensors and AR, we extracted some Instructional design methods (IDMs) from literature which are instructional design patterns that leverage on the expert performance to support training using sensors and AR. IDMs are structured on the concept of capturing the expert performance and using it to train apprentices. Each IDM ("Transfer Mechanisms" in Limbu, Fominykh, Klemke, Specht, & Wild (2018)) is characterised by a description that defines its implementation and the skill that it can be used to train (see

Table 1). The other characteristics include requirements for recording such as hardware and software and requirements, and re-enacting requirements. The list of questions is by no means exhaustible as the IDMs are abstract from domain but using IDMs in the context typically lead to specialisations. IDMs are also abstract from other factors such as the particular vendor sensors. This maintains the abstractness of the 4C/ID model itself which will allows systems to be designed for various domains using the framework. By providing IDMs in each component of the model, the framework assumes that a sensor and AR based training system can be constructed around the models specifications. Next, we provide a general system model outlining the relationship between the components and how the model supports the framework.

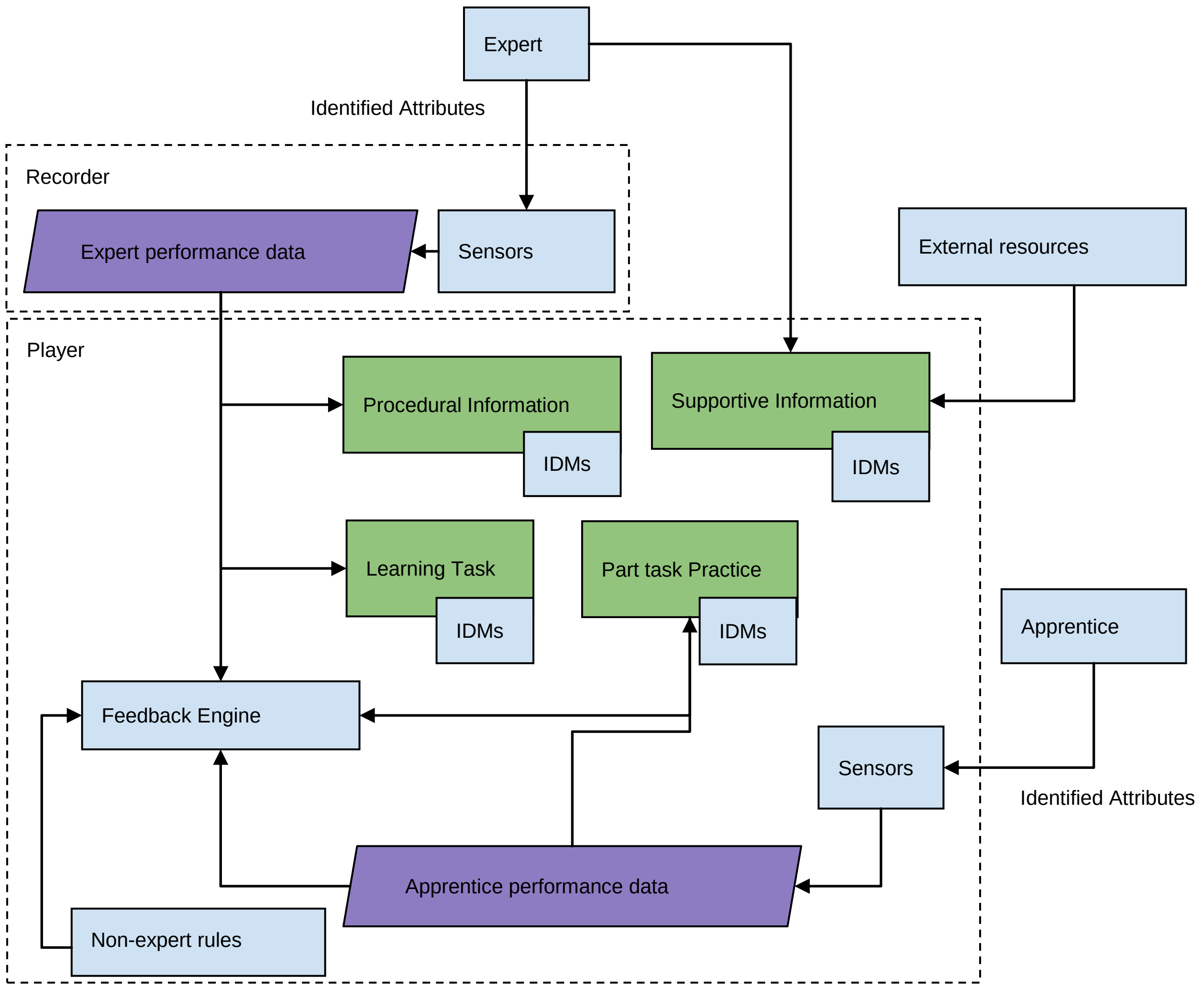

Figure 2: Model of the proposed system for supporting 4C/ID components

The system consists of 2 main components: recorder for capturing expert performance and player for training apprentices based on expert performance (see Figure 2). The capture phase ensures that the expert records all the relevant information needed for the apprentice to perform the task. Rather than capturing raw sensor data, proper attributes of the experts are identified prior to recording, for capture. The captured expert performance is then stored. The player enables apprentices to learn from the recorded performance. The player implements all four components of the 4C/ID model in forms of IDMs which are fed by the expert performance. Learning task component of the 4C/ID model are tasks that the apprentice needs to be perform, for example drawing strokes in calligraphy. Such task may be not necessarily be implemented by the sensors or AR technology unless deemed necessary as the task can the the original authentic task itself. The procedural information component is fed by the expert performance data for providing step by step information on the procedure in just in time fashion. The feedback engine also uses expert performance data to compare with apprentices performance to provide feedback on the attributes during the procedure. The apprentice performance is also stored for reflection in the consecutive sessions to follow enabling the part task practice. Supportive information on the other hand, is provided by means of external resources or allowing expert to create them during demonstration as demonstrated in Figure 2.

Prototype Description: The Calligraphy Trainer

Use case description

The application domain chosen to provide an example for our model, is modern calligraphy. Modern calligraphy relies on fine motor movements of the the hand for producing unique styles of writing letters. The most fundamental aspect of modern calligraphy is to control the pressure applied to the pen in order to control the width of the strokes. As a rule of thumb, heavier pressure is applied on the downward strokes and light pressure on the upward strokes. Some of the common mistakes beginner calligraphers make are that they easily forget to constantly remind themselves to maintain the basic factors such as grip force, posture and angle of the pen. In addition they are quick to lose patience, drawing quick strokes instead of slow steady ones. Beginners in calligraphy are unable to monitor themselves, therefore constant feedback from the expert is crucial to ensure deliberate practice.

Hardware setup

The Hardware setup consists of Myo Armband, Microsoft Surface Pro Tablet and Pen and the Microsoft Hololens augmented reality headset. The Myo armband and the Surface act both as input and feedback systems. The capacitive pen of the Microsoft Surface Pro 2017 and the digitiser on the Surface acts as the main canvas for the apprentice to draw. The surface runs the Multimodal Learning Hub application which acts as the gateway for all sensors applications to communicate. However, it can also be run in a separate pc over the network. The surface also runs the Myo application locally which collects data from the Myo and also provides haptic feedback.

Software Description

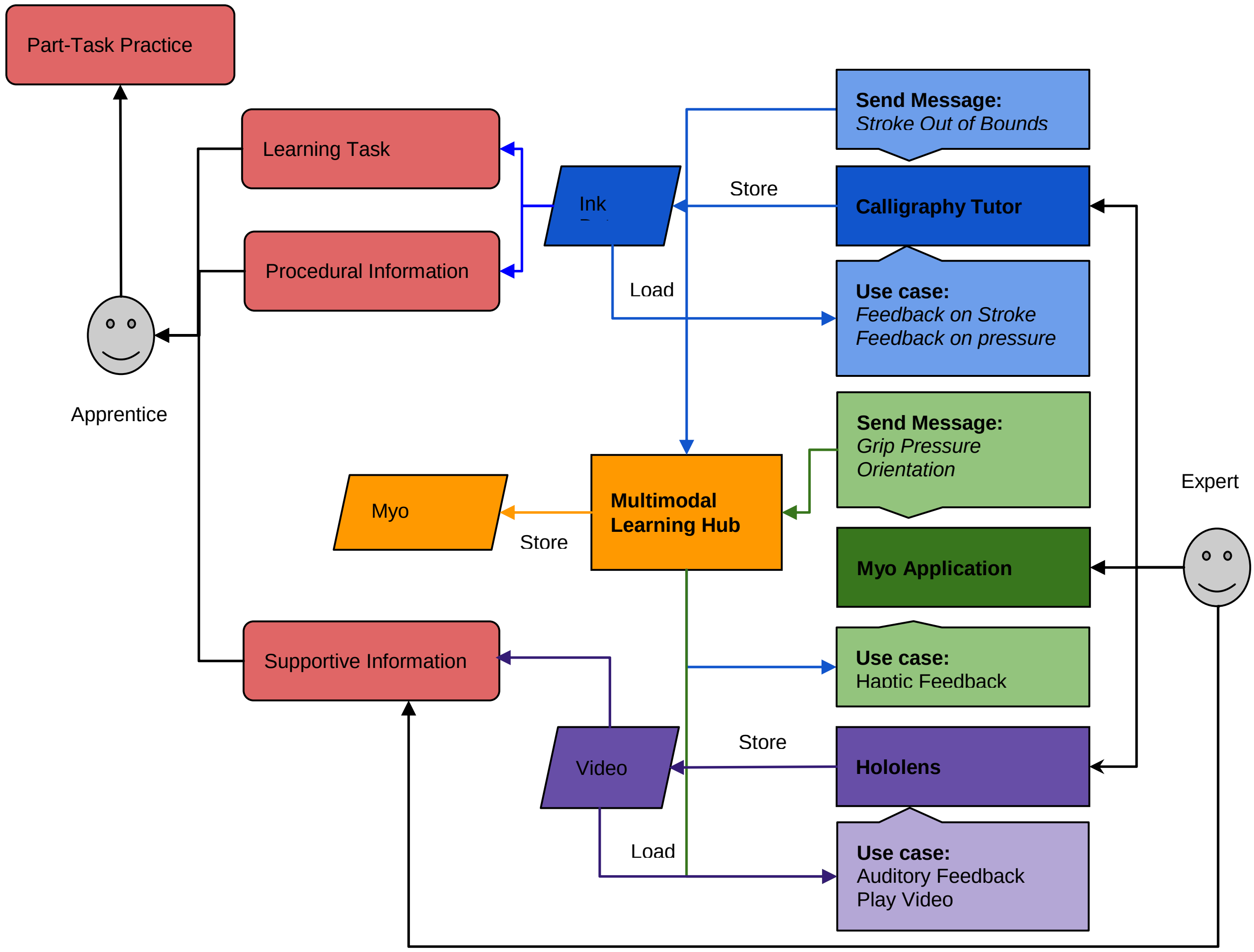

Figure 3: System Architecture

The application was built around the framework defined above, implementing the four components of the 4C/ID model (see Figure 3). For this the system implements IDMs from each component of the model (see Figure 1) depending on the type of attribute relevant in calligraphy. The attributes relevant in calligraphy were identified and are stated in Table 2. Two types of attributes were discovered which are 1. Non-expert based and 2. Expert based. As stated in Figure 2 & 3, non-expert based rules are directly fed into the feedback engine. These rules are fundamental rules and are prioritized when generating feedback. The expert data based feedback are parameters that are recorded from the expert using the sensor.

Table 2: Types of attributes

Non-expert based	Expert data based
• Grip Force • Angle of the pen • Posture of the body	• Pressure applied to the paper • Ink Stroke Hit-test to measure if the same stroke is being drawn • Speed at which the stroke is created

When the expert performance data is recorded, the prototype implements number of IDMs from various components of the framework based on the attributes, ensuring all four components of the 4C/ID model are covered. It should be noted that other types of IMDs can be implemented for a particular attribute. These IDMs are implemented by a combination of 3 different independent applications communicating between each other via the Multimodal Learning hub.

Table 2: Mapping of the attributes with the IDMs

Feedback type	IDMs	Implementation
Learning Task		
Hit-Stroke	Augmented Paths	Displayed on tablet for tracing or imitating, Changing color of the stroke when the color stroke is out of bounds
Procedural information		
Grip Force, Angle of the pen	Haptic feedback	Vibrate myo when the grip is too tight
Grip Force, Angle of the pen	Audio Feedback	Hololens audio reads out the message forwarded by individual application
Pressure applied to paper	Object enrichment	Thickness of the stroke
Supportive information		
Preparation	Cues and Clues	Hololens deployed video
Part task Practice		
Speed of stroke	Summative feedback	Summative results produced

generation, Force, Ink stroke		by comparison to the expert recording

Calligraphy Tutor

Calligraphy tutor is the main application that handles all the lettering for the apprentice. Calligraphy tutor runs on the Surface and collects ink data from the pen. The Calligraphy application has 2 modes. The expert mode for the trainers and the student mode for the apprentices. The expert mode allows experts to draw strokes which can be saved into an Ink Serialized Format (ISF) file. In the student mode, the apprentice can load the data that was saved by the expert without the need to manually annotate the data. This data is used to provide feedback and guidance to the apprentice. For providing non-expert based feedback, for example when the pen angle is too over or under the recommended value, the tutor forwards a message the learning hub which forwards it to the applications which is expecting the message which then performs the corresponding action. For providing expert based feedback in the current time and space, the current algorithm implemented in the tutor breaks down the loaded expert stroke in minute smaller strokes based on the angle between the first vector of each segment and the current vector which is created by iterating through the serialized data (see figure 3). In similar manner, the feedback is provided by comparing the first vector of the student storke with the current vector which is calculated as the student draws the stroke. Based on this comparison, it is determined at which segment in comparison to the expert stroke, is the student currently drawing in and thus, the max and min of the current corresponding expert stroke is used as baseline to provide the feedback.

Figure 4: Expert strokes being segmented in the student mode

Myo application

The myo application is responsible for measuring the grip force applied on the pen, providing the orientation data and providing haptic feedback. The Myo application forwards the orientation data to the learning hub which records the orientation data into a serialized Json file. Locally, the application calculates the grip force based on the emg data and notifies the apprentice by vibrating. It also forwards a message to the learning hub which is forwarded to the listening applications for performing required action such as providing feedback. Myo also receives commands from other applications to provide haptic feedback, for example when the student stroke is out of bounds when compared to expert strokes in the calligraphy tutor.

Holo Calligraphy

This application running on the hololens provides minimalistic feedback to the apprentice. It currently provides audio based feedback after receiving the message forwarded by the applications. The augmented reality display of the Hololens can possibly provide other forms of feedback. Currently, the hololens only provides auditory feedback. Visual feedbacks are obtrusive for the beginners as they require high amount of concentration on the stroke being drawn.

Multimodal Learning Hub

The Multimodal Learning Hub is used to capture data from different sensor-applications. Each of these applications uses different sensors in order to capture different aspects of the learning task. The different sensors measure different properties and operate at different time frequencies; thus each sensor-application generates different type of data and updates it at different frequencies. The Multimodal Learning Hub synchronises and fuses the different streams data generated by the different sensor-applications. It also broadcast feedback messages from the applications for listening applications to process them.

Discussions

In this paper, we presented the theoretical framework for recording expert performance to provide expert based feedback and guidance to apprentices using sensors and AR. The framework is built upon the 4C/ID model which supports complex learning and deliberate practice. 4C/ID assumes that all complex learning can be represented in the form of its four components. In our framework, we complement the model by supplementing each components with IDMs. Our assumption states that if a sensor based learning environment can implement IDMs from each component, then a whole 4C/ID based learning task can be generated. Therefore, we argue that in contrast to learning independently after an initial demonstration by the expert, receiving feedback should foster higher deliberate practice leading to quicker learning of the task.

To explore this, we implemented a proof of concept in the case of calligraphy. The application captures expert performance data and uses it to train apprentices. This approach allows apprentices to receive guidance and continuous feedback based on expert performance, while also allowing experts to easily create learning tasks with the help of the recorder. The expert uses the application in the expert mode to record the learning task, which in case of calligraphy would be some form of stroke.

In the training session, the apprentice logs into the student mode and loads the expert ink data which displays the learning task created by the expert. Guidance is provided in form of transparent animated stroke (see Figure 3). As the apprentice begins to draw the stroke he/she receives feedback based on the expert data and rules hardcoded into the applications (see Table 2). Such feedback is generated by analyzing the stream of data from the sensors by each application, which provides/forwards the feedback when needed. As the apprentice completes the task, he/she is also provided with a overall score as summative feedback, which can assist in reflection for the consecutive practice sessions. The system can also use apprentice data in scaffolding of the feedback provided.

The proposed solution at its current state presents some constraints. As stated earlier in the paper, each implementation of the framework requires identification of attributes which are domain specific and require expert's assistance. After identifying the attributes, the IDMs listed may not cater to the specific scenario. The list of IDMs is an reference list rather than an exhaustive list and is only predicted to grow as the new technologies offer more affordances. In addition, IDMs which use sensors are not capable of measuring tacit forms of knowledge. While tacit forms of knowledge are crucial at higher levels of expertise, we do not intend to replace the expert. The proposed solution only complements the expert in training novices in didactic manner.

Future Work

The prototype needs to undergo an extensive study to test assumed outcomes. Initially, the systems needs to be evaluated to test the usability of the system. The data collected from each sensors needs to be tested for consistency. The algorithms used in providing feedback from the expert data need to be tested for consistent accuracy in the feedback generation.The feedback provided needs to be minimalistic and prioritized and should not hamper the concentration of the apprentice. As such, different modalities should be used in providing feedback when possible and more exploration must be made to enable such feedbacks mechanisms in the system. For example in case of calligraphy, the apprentice is focused on the tip of the pen and using AR displays to overlay information might hamper the needed focus. Proper mechanisms need to be explored to use AR based feedback. Scaffolding mechanism which is crucial to the 4C/ID has not been implemented yet.

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