WIP: Making Implicit Knowledge Explicit – A Data-Driven Approach to Improve Knowledge Transfer in a Glassblowing Beginners Class

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***Abstract*—This work-in-progress innovative practice paper presents a novel approach to 1) extract tacit knowledge from expert trainers while they perform a task demo, 2) decrease the learner's cognitive load via the use of instructional videos portraying the variables at play during a task demonstration, and 3) define quantifiable metrics of expertise by extracting features that differentiate experts from novice practitioners.**

Implicit or tacit knowledge is know-how that experts develop with experience and is difficult to verbalize, formalize or explicitly transfer to others. For this reason, knowledge transfer from expert to apprentice is usually slow and inefficient. Our approach seeks to support knowledge transfer using technology-enhanced approaches. Here, we focus on extracting and describing expertise. We do so by instrumenting experts, trainees and their tools with sensors that can help structure and formalize knowledge. Our first application of this framework is on the knowledge transfer between an expert and novice glassblower. Glassblowing is well known for its crucial expert/apprentice relation and its slow learning rate due in part to the difficulties in verbal transfer of skills. Our framework seeks to capture relevant data while an expert glassblower demonstrates basic actions in a beginners glass blowing course. Our sensors collect eye-tracking activity, verbal demo instructions, pipe accelerometry, air infusion, scene video and muscle activity (EMG), which continuously monitor the expert, their explanations, the tools, and the glass piece. We bring together all the sensed data into instructional videos to be used by novice learners as supportive training material.

We present preliminary results related to metrics of expertise and future steps towards gathering similar data from novices. This will help develop AI-based models to extract data-driven differences between experts and apprentices, which can be used as further instructional material. We will also present plans to test the instructional effectiveness of the developed videos and how our approach can be used in other training settings involving tacit knowledge transfer.

***Index Terms*—Expert-novice; Knowledge transfer; Soft skills**

I. Introduction

The transfer of knowledge from experts to novices is an important human characteristic that has allowed us to preserve and build on knowledge since the beginning of mankind. However, this is not always a straightforward process. Human knowledge can be grouped into either explicit or implicit knowledge [1]. The former can be easily verbalized and formalized into books, manuals or how-to guides, hence it can be readily transferred to others. On the other hand, implicit or tacit knowledge is know-how developed with experience that is difficult to codify or verbalize and hence it is hard to explicitly transfer to others [2], [3]. For this reason, it is commonly seen as a "mysterious" part of knowledge that is usually transferred from experts to novices in educational settings such as apprenticeships through coaching and mentoring.

The expertise in many engineering and non-engineering disciplines relies on tacit knowledge, even in everyday activities such as riding a bike or recognizing a face. This is specially true in tasks that require fine motor skills, hand-eye coordination, and integrating several sensorimotor inputs such as soldering, glassblowing, surgery or sports [4]–[7]. Due to the tacit nature of these activities, knowledge transfer from expert to apprentice is usually slow and inefficient. In this paper we present a new framework to extract and describe expertise to accelerate learning. Our approach consists on instrumenting experts, trainees and their tools with sensors that can help structure and formalize knowledge. Sensing technologies can capture tacit knowledge in a more quantifiable way by grasping details that are not captured by mere observation or verbal explanations.

The idea of capturing tacit expertise in handcrafts using sensors has been explored before. For example in soldering [4], fabrication [8], woodworking [9], pottery [10], [11], crocheting [12], and even embroidery [13]. However, this has never been explored in glassblowing. The first application of our proposed framework is on this type of craft due to its well known tacit component [14].

Glassblowing is a traditional craft passed down through generations and characterized by its intricate techniques. It is well known for its master/apprentice dynamic and the gradual pace of learning, partly attributed to the challenges in verbally transmitting skills. This is because mastering this craft relies significantly on tacit knowledge [5]. There have been past efforts in understanding the tacit component in glassblowing [5], [14], [15], and how to effectively share it [16], but they are all qualitative studies. In this work, we introduce for the first time a framework to obtain quantitative data in a glassblowing hot shop that also allows for the development of instructional videos.

Our framework collects different types of data: eye-tracking activity, point-of-view (POV) video, verbal demo instructions, pipe accelerometry, air infusion, scene video, and muscle activity, which continuously monitor the expert, their explanations, the tools, and the glass piece. We compile all the gathered data into instructional videos intended for novice learners to serve as supplementary training materials. In this work, we share initial findings regarding expertise metrics and outline forthcoming actions aimed at collecting comparable data from beginners. Additionally, we will outline strategies to evaluate the instructional efficacy of the produced videos and explore the versatility of our approach in other training settings involving tacit knowledge transfer. Glassblowing is a traditional discipline with techniques that date back to Roman times, and we hope to upgrade the way it is taught and learned by adapting it to today's technology-enhanced world.

II. Methods

A. Participants

A right-handed expert glassblower, with 25+ years of experience, who is the artistic director of, and instructor at, the MIT Glass Lab was chosen as the study participant. The experiment was approved by the MIT IRB (COUHES) and the participant was provided with informed consent.

B. Glass blowing basics

Manipulating hot melted glass, right out of a furnace (at approximately 1,000 degrees Celsius), is mainly affected by gravity and the temperature of the air, and the material and the tools it comes into contact with. This temperature-gravity dyad drives the glassblowing craft: it requires smooth and continuous rotation of the pipe holding the glass to fight gravity and provide symmetry, and minimal contact between the piece and the tools to conserve the glass' heat. Glassblowing practice requires individual and team skills (see Figure 1). It is a collaborative practice between the "gaffer" (lead glassblower) and their assistant. Technical skills include eye-hand coordination, fine motor manipulation and structured planning. Professional skills include teamwork, communication, collaboration, conflict resolution, and problem solving. Beyond these skills, resilience and patience are key mindsets for a glassblower: the craft's learning curve is slow and a single mistake can shatter, literally, a whole day's work.

C. Sensors

To capture all the relevant information to study glassblowers' expertise, we deployed several sensors in the glass hot shop (see Figures 2 and 3). An important constraint was to minimize disruption to the normal practice of glassblowers in the lab, hence we were required to use sensors with minimal form factors and wireless when possible.

	Skills Mapping for Making a Cup *																												
Skills	Initial shape									Thicker bottom		Initial cylinder		Increase cup length				Cylinder shape				Punti transfer			Open the cup				Finish
Gathering	x			xx																									
Blowing air		x					xx		xxx				x						x		x								
Marvering			x								xxx																		
Blocking			x		xxx		x																						
Heating						xx		xx		xxx		xx		xx		xx		xx		xx		x	x		x		x		
Shapping							xx		xxx				xxx						x		x					xx		xx	
Necking													x																
Swinging															x		x												
Making a punti																						x	x						
Transferring																								x					
Watering																													x

* Every stage requires continuous interactions and professional skills between the gaffer and their assistant

Fig. 1. Basic glassblowing skills mapping for making a cup. Timeline moves left to right. The number of "x" relates to the length of the activity.

- **Eye-tracker.** Knowing where an expert is attending to has been shown to uncover information about their tacit knowledge [17]. Moreover, showing an apprentice a point-of-view video of the tasks to be learned can improve learning [18]. Hence, we recorded eye-tracking activity and point-of-view (POV) video of experts using the Neon portable glasses from Pupil Labs [19]. The system allowed adding prescription lenses for subjects that need correction. Eye and POV cameras recorded at 200 Hz and 30 Hz, respectively.
- **Verbal instructions.** We recorded verbal explanations of the glassblowing expert using the microphone embedded in the eye-tracking glasses. The subject provided instructions as they demoed making a cup.
- **Pipe accelerometry.** Monitoring the pipe's movement is crucial for understanding the expert's technique. We equipped the pipes (blowpipe and punti) with a 3-axis accelerometer to track its rotation and orientation. We used a Puck.js v2.1 from Espruino [20]. We programmed the board to capture data at 30 Hz and to transmit it in real-time to a laptop server using its built-in Bluetooth capabilities.
- **Air infusion.** Air infusion is critical. We installed a magnetic switch in the pedal used to inject air into the glass. The system has a binary actuator (on/off): a magnetic switch to detect whether the pedal is pressed or not. This pedal system was implemented after the pandemic: classical glass blowing is done by directly blowing into the blowpipe. The switch was connected to an ESP8266 board that saved the pedal state at 10 Hz into an SD card. The board's WiFi capabilities were used to obtain the internet unix time for data synchronization purposes.
- **Scene video.** A GoPro Hero 10 camera was set in front of the bench to record a video of the glassblower and the glass piece from the front. This would provide beginners with an additional perspective of the task. The video was recorded at 30 FPS, with 5.3K resolution.
- **Muscle activity (electromyography, EMG).** The hand pressure and gestures with which an expert molds the glass affect the glass piece. Electromyography (EMG) can capture muscle activity in the forearm that correlates with such movements, and it has been proven to show quantifiable differences between experts and novices in other disciplines [11], [21]. We used a Myo armband and the recording

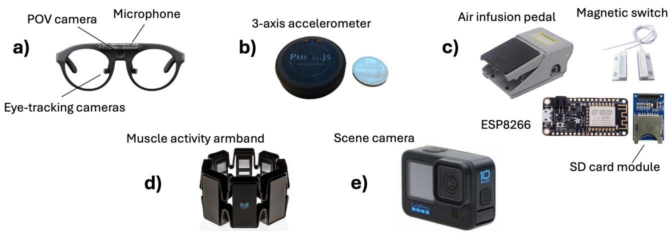

Fig. 2. Sensors used by our framework to monitor the different variables at play during the glassblowing practice. a) Eye tracking glasses including POV camera, microphone and eye tracking; b) 3-axis accelerometer; c) air infusion pedal with hall effect switch and micro-controller to record and store data; d) 8-channels EMG arm band; and e) GoPro frontal scene camera.

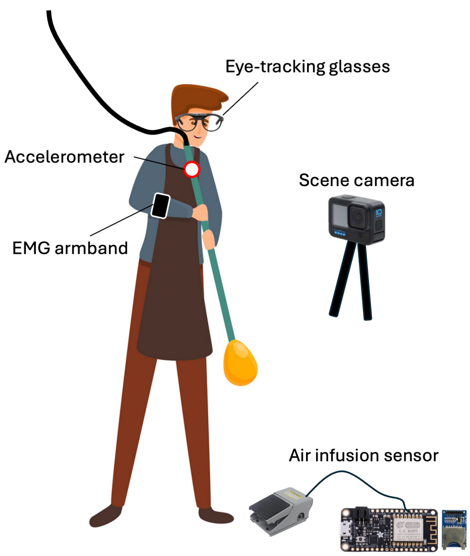

Fig. 3. Glassblower with the wearable and external data collection sensors.

framework from [22] to log the muscle activity data via 8 differential EMG channels, recorded at 200 Hz.

III. Pilot Study

A. Experiment design

The experiment consisted of the instructor performing a demonstration of the beginners class, which involves the making of a cup. The participant was asked to complete the demo as usual, providing verbal explanations and clarifications of each step. While doing so, all the sensors listed above (see Section II-C) were activated and monitored the corresponding data. The data collected would be later synchronized using the logged timestamps.

B. Instructional video

A key element of the instructional video is to be able to show the glassblowing activity from the glassblower's point of view. By doing so, the apprentice would become acquainted with the activity from the perspective they would encounter in the real world, an experience not typically provided in traditional classes nor in the regular glassblowing

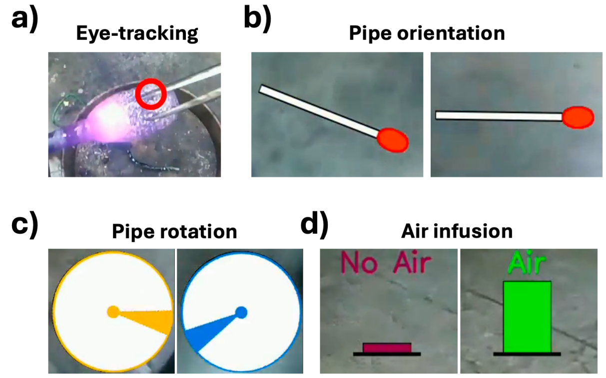

Fig. 4. Video screenshots of the different animations that convey the critical glassblowing variables sensed. a) Eye-tracking and POV as seen by the subject; b) pipe orientation provided by the accelerometer; c) pipe rotation from the accelerometer, describing yellow and blue as clockwise and counter clockwise rotation, respectively; and d) air infusion from the pedal sensor presenting the entrance of air into the hot glass.

training model. Moreover, research has shown that point-of-view videos presented to apprentices can improve learning [18]. For this reason, the point-of-view video was chosen to be the backdrop and center of the instructional video where all other data would be displayed on. A red circle overlayed on the video continuously shows the gaze of the glassblower (see Figure 4).

To convey the information captured by the rest of the sensors, different time-locked visual animations were rendered around the video (see Figure 4). An animated pipe shows its orientation angle with respect to the horizon. A rotating wheel shows the rotation speed of the pipe, and its color (yellow or blue) represents the direction of rotation (clockwise and counter-clockwise, respectively). A moving bar shows when the air pedal is pressed (green bar) or not (red bar). Text and color change with the pedal state. Finally, a synchronized video from the frontal scene camera was overlayed on the top left corner, giving a frontal perspective of the craft. Overall, we intended that the sensor information is conveyed in a simple and visual way, for the apprentices to assimilate it more easily. A frame of the instructional video, together with annotations of the corresponding video elements is shown in Figure 5.

C. Preliminary data analysis

A preliminary sensor data exploration allowed us to visualize and quantify a sign of expertise when it comes to handling the pipe. As explained earlier, gravity is always acting on the melted glass, so it is crucial that the glassblower constantly rotates the pipe to compensate its effect on the piece. To make sure that the center of mass of the piece is always aligned with the pipe axis, maintaining a constant and sufficient rotation speed is a skill that experts implicitly internalize. Analyzing the accelerometry data of the pipe, we can see that the expert managed to sustain a very constant angular speed while handling the pipe, regardless of the direction of rotation, with also a constant and low standard deviation, as seen

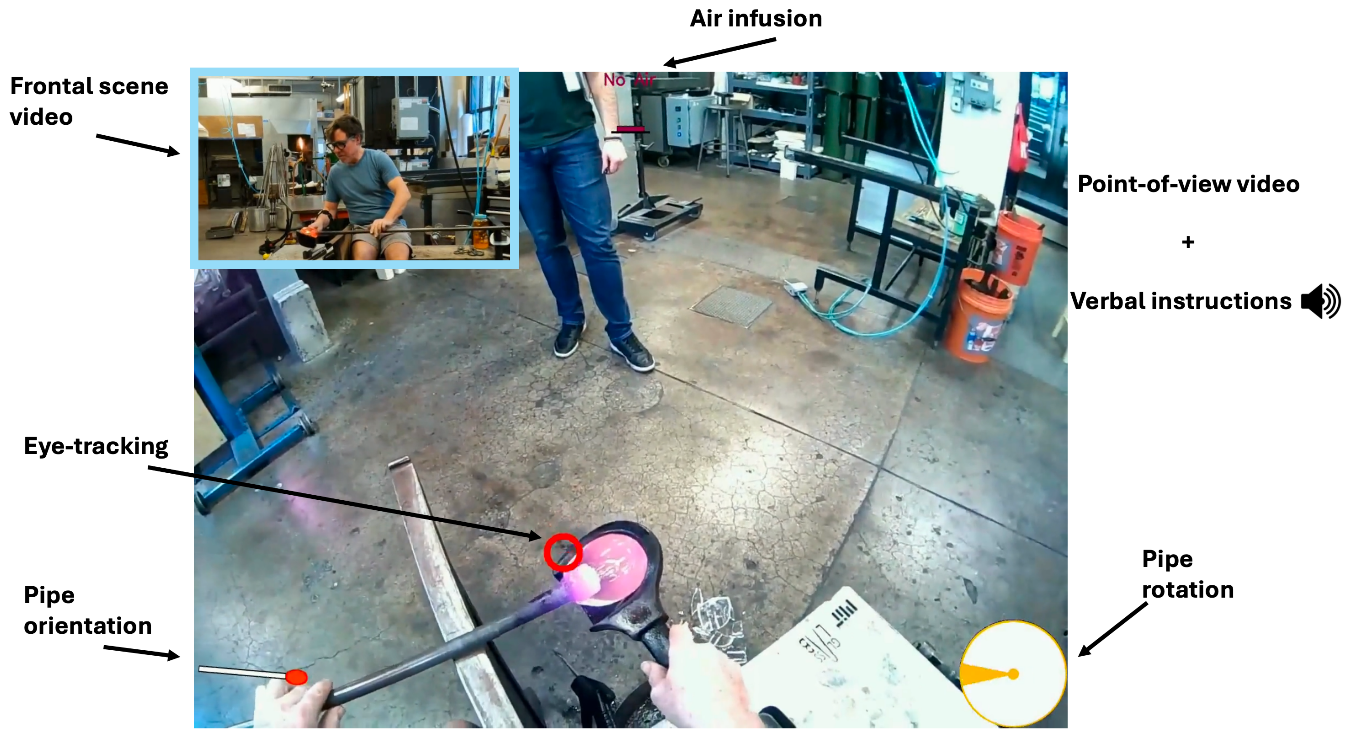

Fig. 5. A frame of the instructional video.

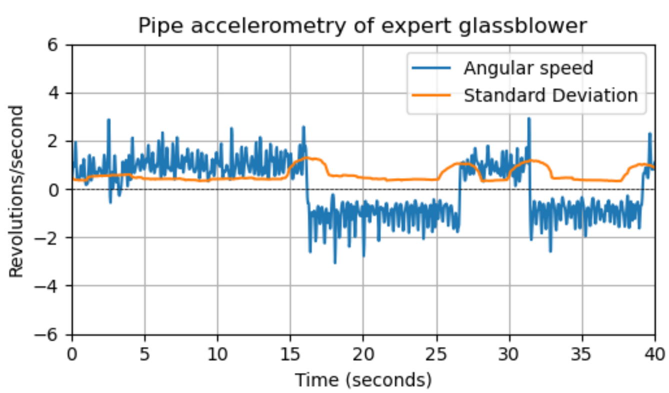

Fig. 6. Pipe accelerometry plot of 40-second window data collected from an expert glassblower. Angular speed was obtained by computing the derivative of the unwrapped roll angle of the pipe. We can see that the expert maintained a constant angular speed of around 1 revolutions per second regardless of the direction of rotation. The standard deviation of the angular speed was computed with a rolling window of 3 seconds, which is maintained under 0.5 rev/sec.

in Figure 6. Angular speed with standard deviation are two examples of quantifiable metrics that can be eventually used to assess glassblowing expertise and to help train beginners with more explicit instructions and feedback (i.e. giving haptic feedback to learners to inform them in real-time when the pipe's acceleration is fluctuating).

IV. Future Work

There is an important amount of future work to be conducted. First, we plan to empirically test the effectiveness of our framework by comparing the performance of students who received the instructional material with those who did not. We aim to run a randomized controlled trial, clustering learners into two groups, and creating two different skills-gains metrics. One will be based on a rubric co-created with the instructors regarding the basic skills to be acquired during the beginners class. Instructors will then evaluate all learners using this rubric. The other metric will be a self-assessment questionnaire of the glassblowing skills for learners to complete. We aim to collect these data from both the group having access to the sensor-informed instructional methods prior to their classes (intervention group), and the other group that will be only exposed to the traditional mode of instruction (expert live demo and expert support during class). We expect the results to provide insights into real learning gains (through instructor skills evaluation) and the learners' perceived learning gains (via the self-assessment).

Second, we will collect sensor data from beginners performing similar glassblowing tasks. Having sensor data from both experts and novices can help to further understand and formalize expert knowledge. With the gathered data, we plan to construct AI models to discern data-driven differences between experts and novices, which can subsequently be used to enhance instructional resources.

Finally, we would like to expand our framework to other disciplines characterized by the reliance on tacit knowledge, such as sports like table tennis or squash. We believe that by exploiting similar sensor based data and with custom feedback, we can make the teaching and learning of such sports more efficient.

V. Conclusions

This work in progress paper presents a new framework to extract tacit knowledge of experts by instrumenting their bodies, tools, and other objects of interest using sensors that capture relevant expertise-related variables. Quantifying and formalizing their knowledge is a crucial step to improve how their skills are transferred to novices and accelerate their learning. We tested this framework in the context of glassblowing, since it is well known for its slow learning rate due to the difficulties in verbal transfer of skills between instructor and apprentice. This resulted in the making of instructional videos that convey the sensed information in a visual and distilled manner so apprentices can internalize the different variables at play effortlessly.

Tacit or implicit knowledge transfer is a current challenge in the context of STEM education. The slow learning curve to becoming proficient in certain skills makes such training a resource intense practice, both regarding learner and instructor time, and access to qualified experts to guiding the learning journey. The current teaching practice has revealed a scarcity of expertise in several domains of scholarship. This paper provides some first steps towards tackling this problem: it proposes a framework to extract and record an instructor's expertise (i.e. instrumenting a task demonstration), creates resources to more widely disseminate it to students (i.e. develop tailored instructional videos), and suggests methods to better provide real-time feedback to novice learners (i.e. instrumenting the learner's performance and creating metrics of expertise). Through this approach we aim to make implicit knowledge explicit.

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