Expressive Robotic Patient Simulators for Clinical Education

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Abstract

Robotic patient simulators (RPS) are the most commonly used robot in clinical education, and provide low-risk, high-fidelity learning experiences. They are life-sized humanoid robots that can simulate human physiological responses. Commercially available RPSs lack realistic facial and social cues, which limits their ability to engage human learners and immerse them in the simulation. This may cause poor skill transfer, which can result in adverse patient outcomes. We address this by introducing an expressive RPS capable of conveying expressivity far beyond the state of the art, including pain and neurological impairment, as well as a new shared control system to support clinical educators. This paper presents our ongoing work, and discusses its implications for the HRI and medical education communities.

Introduction

In clinical education, simulation serves as a valuable component to experiential learning at all stages of one's career [2]. Simulations enable learners to practice their communication and procedural skills in a safe, clinically-similar environment without the fear of harming real patients [10]. These skills may include: patient communication, patient condition assessment, and procedural practice [6, 12].

One of the most commonly used modalities in simulation are robotic patient simulators (RPS), which are lifelike android robots that convey realistic patient physiologies and pathologies. RPSs have been explored in a wide variety of HRI applications [11,13]. RPSs provide clinical learners with an active learning environment to practice different skills without harming real patients, and to explore risky clinical scenarios through teamwork experiences. Research shows that using these simulators increases comprehension, confidence, efficiency, and enthusiasm for learning [2]. Furthermore, their usage may reduce preventable medical errors, which kill approximately 400,000 people per year in hospitals alone, and are the third leading cause of death in the United States [1, 6].

Although using RPSs has a positive influence on the learners' experiential learning performance, current commercial simulators suffer from a major design flaw: they are completely lacking in facial expressions (see Figure 1 (center)). Our prior research suggests this lack of facial expressivity may lead to adverse patient outcomes [4]. Non-expressive RPSs break immersion, and may be distracting learners from fully engaging in simulations, or may cause them to learn the wrong skills, which could create future problems in how their learning transfers to real clinical spaces. Another challenge to existing systems is their usability and controllability. Work by our team and others also shows that current RPS systems are difficult for educators to control, particularly when running more complex simulations [5, 6].

Our work addresses these limitations on two fronts. First, we are designing an expressive, low-cost, interactive RPS which will integrate with existing simulator systems. It has a wider range of expressivity than commercially available systems, including the ability to express pain, neurological impairment, and other pathologies in its face [6], thus

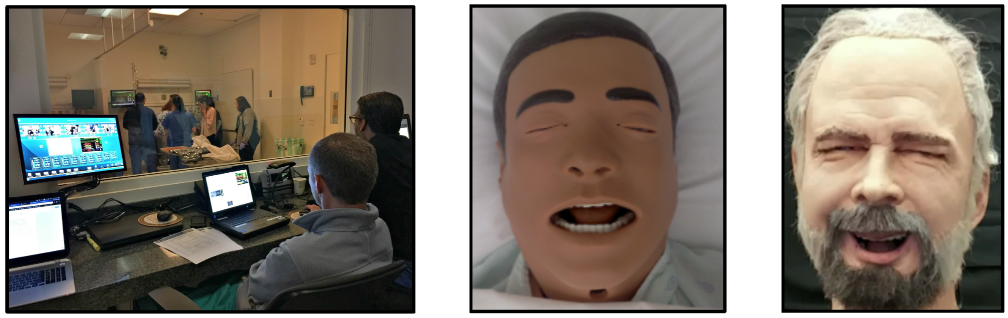


Figure 1. Left: Simulation center setup where a team of medical learners treat a non-expressive RPS that is controlled by a medical simulation operator sitting in the operating room. Center: An example of a commonly used inexpressive mannequin head. Right: An example of an expressive RPS system our team built, that our team built which is synthesizing pain.

more engaging with learners. Second, we are designing a customizable shared control system which will help reduce operator workload and improve their ability to focus on educational goals rather than robot controls. This paper discusses our continuing work to date in this area.

Expressive Robotic Patient Simulator

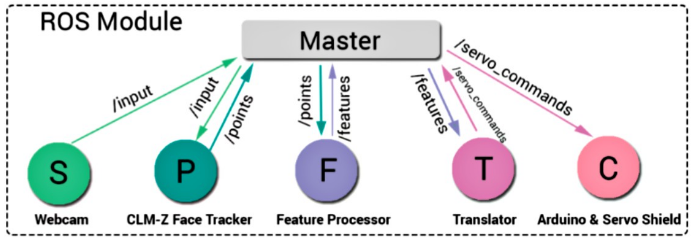
Despite the critical importance of facial expressions in real life scenarios where nonverbal cues are crucial for treatment, current RPSs exhibit static faces, and are unable to convey any form of facial expressions. Humans communicate a great deal of information through nonverbal means; therefore, RPS systems need to be capable of recognizing, masking, and synthesizing nonverbal behaviors, such as facial expressions to convey realistic interaction between a human and robot [6, 7]. Moreover, having an embodiment for expressivity has been shown in the literature as an effective means for communication facilitation between people and robots [3]. To date, this topic has been underexplored in the literature, particularly within the context of real-time RPS interaction and control. In our work to date, we have made the following contributions: developed an automatic method for real-time facial expression synthesis on physical robots or virtual avatars [9] and conducted several studies to validate our synthesis approach [6, 7]. These are summarized briefly below.

Real Time Facial Expression Synthesis

One of the main challenges in facially expressive robots is how to synthesize human-like expressions generally, in a way that is platform independent and adjustable to different control paradigms. To aid the community, we introduced a generalized automatic framework for synthesizing the facial expressions on different synthetic faces in real-time, which we implemented as a Robot Operating System (ROS) module [6, 9]. Our synthesis method is based on performance-driven animation, which maps motions from video of an operator/educator onto the face of an embodiment (e.g., virtual avatar or robot).

Figure 2 shows an overview of the framework. It is a ROS module which performs synthesis as follows: After sensing operator's face with Sensor, S, we use a Constrained Local Model (CLM)-based face tracker as a point streamer, P, to publish the extracted facial points from the sensed face. A feature processor, F, subscribes to the published information, measures the distance of each facial point to the tip of the nose, and saves 68 distances in a vector to keep track of any changes as extract features. Next, a translator, T, converts the extracted features to either the servo motor commands of physical platforms or the control points of a simulated head. Finally, a control interface, $C : C_1 ... C_n$ makes a readable file for the robot, containing the movement information and sends it to the robot to control points on a virtual face or actuate motors on a robot. Using this framework as the software for our bespoke RPS head, our robot can easily synthesize patient-driven expressions and pathologies on any robotic heads or avatar, and adjust to varying degrees of freedom (DOF) [8, 9].

Figure 2. Overview of the proposed method from [9]. Nodes: (1) webcam: records RGB data, (2) CLM-Z face tracker: tracks human faces, (3) feature processor extracts facial features, (4) translator maps feature points to control points on the physical robot or virtual avatar face, and (5) arduino and servo shield moves the control points.



Robot-Centric and Human-Centric Method Validations

To date we have run a series of robot-centric and human-centric experiments validating the effectiveness of this technique for understandable, synthesized, generalizable expressions on both robots and virtual characters. One robot-centric evaluation included a series of similarity tests between the input stream of the operator's face and ultimately actuated synthesis on the robot (see details in Moosaei et al. [8, 9]). Our results suggest that our method can accurately map operator facial expressions to both simulated and robotic faces, and can also operate in real time.

Our most recent human-centric study is described in [6], where we explore how clinicians and non-clinicians perceive painful facial expressions synthesized on a virtual character vs. a 21-DOF android robot. Using the autonomous synthesis techniques described previously, we synthesized pain on a humanoid robot and comparable virtual avatar. Our experiment included 51 laypersons and 51 clinicians. The goal of our study was to compare pain perception across the two groups, and explore the effects of embodiment (robot or avatar) on that perception [6].

Our results showed that clinicians had a lower overall accuracy in detecting synthesized pain in comparison to lay participants. This finding was consistent with the medical education literature, and suggests RPS technology may provide additional opportunities to train (or retrain) clinicians in patient pain perception. Interestingly, our results also showed that participants were less accurate overall when detecting pain from a humanoid robot compared to a virtual avatar [6]. This suggests a multimodal approach to using RPSs in clinical education may be beneficial, a question we will explore further in our future work.

Shared Control for Clinical Educators

Clinical educators have inherently challenging jobs controlling RPSs given the current state-of-the-art. They typically sit at control stations watching learners (see Figure 1 (left)), manually changing physiological parameters of the RPS on the fly depending on the clinical choices learners make. Thus, this is a dynamic learning environment within which the introduction of autonomous behavior and new functionality must be carefully considered. Thus, it is critical to carefully study the current ways in which educators work during simulations in order to best support any changes to their workflow.

We are closely collaborating with a team of clinicians, engaging in an iterative design process, to create a new shared control system for the RPS. The system will support a range of adjustable control modalities, including direct teleoperation (e.g., puppeteering), pre-recorded modes (e.g., hemifacial paralysis in stroke mode), and reactive modes (e.g., wincing in pain given certain physiological signals)

As part of our design process, we are engaging in interviews with clinical educators and learners, as well as conducting observations of live simulations at the UC San Diego Simulation and Training Center. Learners include a range of professionals at various stages of their careers, including junior trainees (e.g., medical students, nursing students), as well as senior clinicians undergoing retraining and re-certification (e.g., anesthesiologists, attending physicians). Thus far we observed a series of neurological

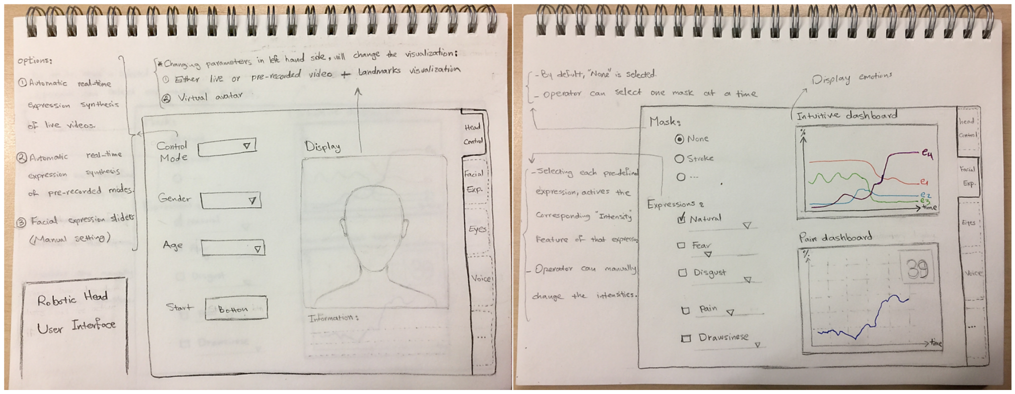


Figure 3. Initial designs of the shared control system for clinical educators. We are engaging in an iterative design process with educators and learners.

assessment simulations, where learners are required to practice both procedural and communication skills during the course of their interaction with the RPS.

To date, we have observed several ways in which the RPS is used, including when it is talking and interacting with clinicians, as well as when it is only briefly awake before undergoing anesthesia. These observations led to our initial designs (See Figure 3), which included both autonomous control (to keep complexity low while clinicians are attending to other tasks), as well as supervisory control to support more nuanced changes in expressivity.

One goal in the design of our system to be able to autonomously display facial expressions based on other biosignals on the RPS. This is ideal for either predefined scenarios where little will change during the simulation, or when operators are able to pre-assign states to the robot while attending to other tasks. For example, while learners are focusing on trying to determine a proper amount of medication to administer, the operator can instruct the robot to respond with a series of set expressions depending on the selections the students make. The operator can then focus their attention on planning for how the RPS will respond to various medications. Another advantage of this is if the educator is distracted they do not need to worry about where their facial position is relative to the camera.

Another goal is to support automatic real-time mapping of the operator's live video to the robot's face using the aforementioned performance driven synthesis system. This may be useful in cases where unpredicted conditions occur while running a predefined scenario. To use the previous example, if the learners administer a completely wrong medication, causing the RPS to go into anaphylactic shock, the operator may want to create a new set of responses on the fly to match that outcome.

Finally, our system will also support direct manual control of facial expression sliders (e.g., one slider for each of predesigned expression mode). This can allow operators to generate simple expression, such as closing the eyes to simulate an unconscious patient.

Discussion and Future Work

Our work explores how to make simulators more diverse, interactive, and immersive for clinical learners in a simulation educational setting. In our work to date, we have developed an automatic method for real-time facial expression synthesis on physical robots or virtual avatars [9] and conducted several studies to validate our synthesis approach [6, 7]. We also have fabricated a new, low-cost expressive RPS head which is capable of conveying patient pathologies, and have begun co-designing a shared control system with clinical educators.

In the coming year we plan to run a series of experiments testing the new RPS and control system with clinical educators and learners to evaluate its effectiveness in real world learning environments. We hope this work will help improve the state of the art in clinical education, as well as help us explore HRI in new experiential learning settings.

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