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AIMS: Applying Game Technology to Advance Medical Education

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The Automated Intelligent Mentoring System (AIMS) takes clinical procedural skill acquisition to the next level by replacing subject matter judgment with precise measurements.

Medical procedures, if performed incorrectly, can have serious and sometimes fatal consequences. For example, a misplaced airway tube could result in a patient's death. The importance of deliberate and repetitive practice and feedback are well recognized as key features effective in learning via high-fidelity medical simulation,[1,2] particularly in the acquisition of clinical procedural skills. To provide adequate opportunity of these key features, learners must have access to appropriate simulation devices, equipment, faculty mentoring, expertise, feedback, and individualized time to acquire a designated skill to the defined level of competence or mastery.

Although this model is achievable, it comes at a high cost. In some cases, this limits the opportunity for learners to have adequate, individualized opportunities to achieve desired performance outcomes. As clinical demands increase on medical educators, the availability of their time to observe, mentor students, and provide meaningful corrective feedback is becoming more difficult. Finally, faculty observations of clinical procedural skills rely mainly on subjective criteria regarding the actual precision of real-time human performance metrics. The objective measurement of these human performance metrics is a "missing middle," both in terms of simulator(s)' and faculties' ability to provide corrective feedback to aid in the acquisition or performance improvement of procedural skills.

The project described here could substantially contribute to solving this training dilemma and provide new levels of human performance feedback and data related to clinical procedural skill acquisition and performance improvement. The Automated Intelligent Mentoring System (AIMS) was developed by Eastern Virginia Medical School (EVMS) and SimIS for teaching and rigorously assessing procedural clinical skills performed by both novice learners and highly skilled professionals. AIMS is a low-cost system focused on the measurement of human performance related to specific real-time, 3D psychometric measurement of clinical procedural skills. Simply put, AIMS utilizes the Microsoft Kinect camera to observe and record experts demonstrating clinical procedural skills, creating a baseline for mastery-level performance. The camera then observes students practicing this skill, compares their performance against the mastery-level baseline, and provides feedback when he or she needs help or makes a procedural misstep. AIMS is able to provide professional instruction with individualized, autonomous feedback for the learner, while providing detailed performance analytics for the instructors to remotely analyze, react, and refactor their future instructional efforts.

Overview of AIMS

AIMS, in its current form, is an advanced prototype undergoing testing and validation before it's ready for commercial distribution. EVMS and SimIS have submitted a patent application to the US Patent Office (PCT/US2013/032191) for this technology. From the medical domain side, students of EVMS help in evaluating the efficiency of AIMS for medical education, while computer science students from Old Dominion University (ODU) are providing code reviews, dry runs, and stress tests.

Figure 1 shows the original planning, as submitted to the US Patent Office. The clinical procedure is conducted on a medical mannequin, shown in the lower part of the figure. The Kinect camera is used to observe the procedure, while the AIMS software conducts several computational tasks:

- It converts observations from clinical experts into an aggregated mastery model.
- It observes and compares learner performance with the mastery model.
- It provides feedback to the learner in the form of scores.
- It activates learning modules by voice (learning modules can also be triggered by observed mistakes).
- It manages scores for learners and educators.

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AIMS employs the Automated Intelligent Mentoring Instructor (AIMI) to provide verbal feedback and learning sequences. The sequences are delivered to the learner as prerecorded videos, previously rendered animations, or verbal interjections upon request. While the current version of AIMI is presented in English, the design of the text-to-speech system is multilingual. AIMS also utilizes cloud-based services for data storage, the release of new training modules, and software updates.

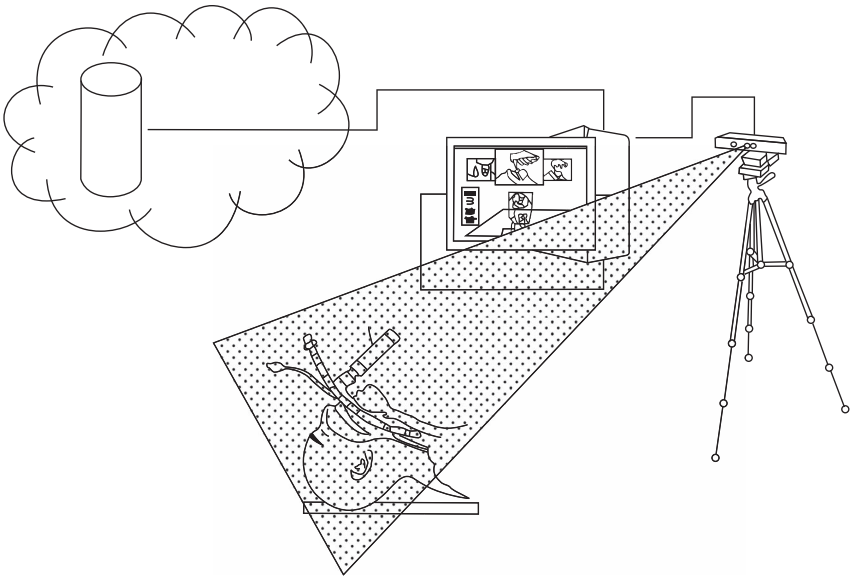

Figure 1. Schematic representation of the Automated Intelligent Mentoring System (AIMS). The Kinect camera observes the procedure and feeds the data to the computer, which then compares the observation with the mastery performance model and provides feedback.

Creating Mastery Performance Models

The mastery performance models developed for AIMS can be divided into three categories. The first category focuses on independent skill acquisition and assessment. AIMS is designed to support clinical procedural skill acquisition based on a best practice model for each clinical procedure taught by subject matter experts. The ideal mastery performance model is validated by recording a minimum of 10 expert clinicians over the course of 10 or more concurrent procedural runs. These procedural runs are recorded using the Kinect camera, focusing on tracking the human performance and instrument manipulation to ensure construct validity and variations of technique. Each run results in several Bezier curves (that is, paths of procedural mastery), showing where each instrument should be in space and time. The measurements are then calibrated to fit a common scale, the recordings are aggregated, and the results refined to become the mastery performance model, which accounts for allowed discrepancy intervals (for example, variations in technique between experts, which have no bearing on the outcome).

If the clinical procedure is conducted with medical instruments, observing the placement of those instruments through color tracking and path comparison is currently the ideal capture method to achieve the most accurate performance results. This specific technique was used for mapping the endotracheal intubation (introducing a tube through the mouth into the windpipe) mastery-performance model. Endotracheal intubation has a specific order of operations and handedness (which hand to use for which activity) of instrument manipulation. To perform the procedure correctly, the clinical expert or learner tilts the patient's head backward into a sniffing position to obtain a proper viewing angle, which consists of the oral, pharyngeal, and laryngeal axes to align.

The participant then inserts the laryngoscope with their left hand to hold the tongue out of line of sight to view the vocal chords and provide access to the windpipe. Next, he or she grasps and introduces the endotracheal tube into the windpipe and removes the laryngoscope out of the patient's mouth. Finally, he or she inflates the attached balloon cuff using a sterile syringe, removes the stylet from the endotracheal tube, attaches the valve bag to the tube, and begins ventilation on the patient.

The mapping process applied to endotracheal intubation can be applied to any procedure with well-defined criteria and observable actions for adequate or mastery performance.

In the learning mode, procedural steps are explained in detail by AIMI. AIMI serves as the training system's proprietary autonomous learning instructor inside the AIMS system. In Figure 2, AIMI guides the learner through the steps of how to grasp the endotracheal tube with the right hand after the tongue is trapped by the laryngoscope and fixed with the left hand.

The second mastery performance model category of clinical procedures requires tracking a learner or learners within the group training environment and not just the instruments. In this case, some additional scaling is needed, as human body parts aren't standardized in length, mass, or color. The paths of procedural mastery during the same clinical training exercise

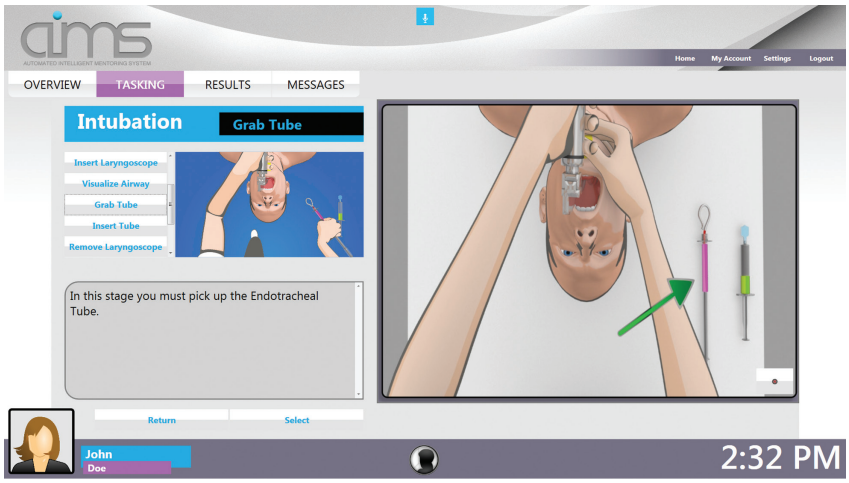

Figure 2. Example of AIMS learning mode with AIMI interaction. AIMI guides the learner through the steps of how to grasp the endotracheal tube with the right hand after the tongue is trapped by the laryngoscope and fixed with the left hand.

conducted by a 6′6″ tall expert, will differ significantly from the one conducted by a 5′4″ tall expert. Although the movements might be on a different scale, morphologically they should be identical.

An example is the performance of closed chest compressions during cardiopulmonary resuscitation (CPR). To ensure accuracy of assessment metrics across a wide range of human morphologies, scaling within AIMS is required to account for differences in body size and shape as compared to the mastery performance model. For example, the physical distances between fingers to wrists, wrists to elbows, and elbows to shoulders are unique to each individual performing the skill of closed chest compressions. Through AIMS scaling features, each individual can be equally compared to the mastery performance model.

The third mastery performance model category requires the tracking of teams of two or more learners. In this type of model, multiple individuals' performances are tracked and assessed to determine individual performance metrics and their impact on overall group performance. This category requires the tracking of two learners and the capture of the choreography of their actions in the performance model. Expert capture sessions in the clinical environment must include the proper distance between team members and include nonverbal cueing and communicative gestures.

In addition to the challenges of tracking the data described in the three types of mastery-performance models, tracking of specific vocal interactions via directional microphones built within Kinect is possible. For example, speech recognition checks whether the learner is communicating with the patient, assigning someone to call 911, or requesting an automated external defibrillator (AED). This feature is also the mechanism for requesting assistance from AIMI.

Computational Challenges

Within *CiSE*, computational challenges are likely the most-looked-for section. As part of the work has been submitted for a patent, we hope that the details we provide here are sufficient to communicate the unique challenges of this project. Replacing subject matter judgment with precise measurements was one of the driving objectives. This approach itself is a small revolution, as currently learners are evaluated by instructors based on subjective observation. What we wanted to do is observe the learner, map his or her clinical procedure activities to the mastery model, check if the observed differences are critical for the clinical process, and provide measured objective feedback. Using the Kinect to do this wasn't as easy as expected.

As discussed previously, the first type of mastery performance models require the precise tracking of tools and their position in space. To gain this capability, the OpenCV computer vision library was used—specifically, the image-processing features of the library.

Recognizing objects such as clinical instruments just based on their shape proved to be too rigorous for the intended application. To ease the artificial recognition of objects that must be tracked by the system, such as specific anatomical areas of the mannequin and medical tools, instruments, and devices, colored stickers are placed on these objects. Instead of recognizing the object, we could now recognize the color code to get a first visual queue. Within AIMS, the objects are then located in the scene by scanning each color frame from the color stream for the indicator markers. In Figure 2, the tools are marked with special colors. These colors allow AIMS to locate specific objects or features within an image and evaluate the position. A single color may be used to track or assess multiple objects within the training environment and identified on a per-stage basis. Using the colors resulted in a significant improvement of recognition speed. One unexpected challenge we faced involved the neon-pink fingernails of one learner in the first test; a problem that could be solved by surgical gloves.

The next challenge was that the exact coding of the colors is highly dependent on the artificial light used. The Kinect doesn't work well in rooms with an abundance of natural sunlight

and won't work with direct sunlight. The challenge is then to calibrate the system to recognize the temperature of the light in the room and identify the appropriate colors correctly before starting any training or practice session. Though ultimately, automating this calibration for the user in a range of lighting environments wasn't a simple task. One of the common research projects with students of ODU was to facilitate this process with the use of color-tracking software. The color-tracking tool references a collection of calibrated colors and value ranges. These value ranges span hue, saturation, brightness, and temperature, and by doing so, the ranges take into consideration the associated lighting conditions when the learner works with AIMS.

The next challenge was tracking the movement of learners. The Kinect is generally used for large broad or fluid movements akin to dancing or moving in action games, leveraging hands-free user interfaces. More recently, the technology has been used for scanning physical objects to create 3D meshes of those objects. Our use of the Kinect strayed from these de facto norms, and required an intricate implementation process. The ability to measure the specific and individualized actions of each unique learner was pivotal to reaching the objectives described for AIMS. These actions are broken down into key movements, measurable by trends in skeletal movement. The Kinect Software Development Kit (SDK), available from Microsoft, was used to identify positions of skeletal joints and bones, providing a means to measure skeletal movement—but this was insufficient for high-fidelity tracking.

To retrieve the movements of experts and learners and relate those to procedural actions captured in the mastery-performance models, the fidelity of the Kinect's skeletal data had to be improved beyond the default settings and software development kit's (SDK's) abilities. The Kinect SDK enables developers to identify smoothing parameters associated with the skeletal data provided from the sensor. The effects were examined by altering these smoothing parameters to optimize tracking of concise movements as identified by our subject matter experts. By default, the sensor reports smooth approximated movements, which work well when broad movements are required or when displaying user interface feedback, but not as well when analyzing concise particular movements. The goal was to identify smoothing parameters that could deliver raw enough skeletal data excluding anomalies, without noticeable latency. Precise measurements can now be made, but they still lack the ability to identify coherent movements or visual clues, as described in the last section.

The naive approach would be to break a procedure down into a series of snapshots. When observing such snapshots without additional information on causality and constraints of joints, the amount of possible transitions between snapshots grows exponentially with the sum of tracked objects and related phases of the procedures. This again would lead to unnecessary computing and unacceptable time delays. To address this challenge, a utility must be created to collect and analyze skeletal joint history—that is, skeletal joints over time. This utility exposes trends of movements and provides a means to identify key movements, classifiable as a particular action. A change in trend could identify the continuance of an action consisting of multiple movements, improper implementation of an action, or the commencement of a new action. To instill further confidence of expected actions, kinematics are utilized and multiple checks comparing the skeletal data to ensure the suspected action(s) are possible with the users' instantaneous position. The ability to identify processes and use their measurements allowed us to create the mastery-performance models and then to use for comparison of the individual learners' evaluations.

The next challenge was to identify a particular learner within a crowd—in other words, to tell AIMS which individuals in a group should be evaluated. The Kinect SDK allows full tracking of two skeletons at once, with joint and bone positions, and up to six skeletal-only positions. This idea was extended, as Figure 3 shows, to support tracking individual learners as well as individual learners within a team by introducing a "sticky skeleton" and "sticky gestures." When the tracking process starts, every incoming frame from the skeleton stream is sampled for "sticky gestures." In the examples, the gesture was the raised arm. If the "sticky gesture" is present, the skeleton exhibiting the qualifying gesture becomes a "sticky skeleton." This is repeated until the expected number of skeletons are identified, and the others are discarded.

Another challenge was that the Kinect sensor would periodically lose a user's skeleton. To avoid having to go through an initialization cycle again, a persistence capability was developed, which redesignates sticky skeletons without requiring the user to perform another sticky gesture. Plainly, sticky skeletons—which are lost in the scene when the user hasn't exited—are restuck automatically without action from that user. This

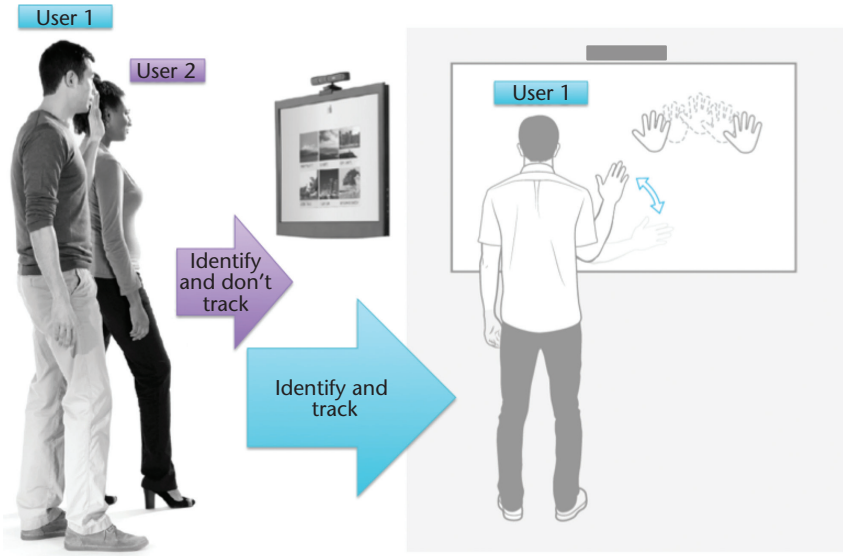

Figure 3. Identifying and tracking single users from a group via "sticky skeleton" technology. When the tracking process starts, every incoming frame from the skeleton stream is sampled for "sticky gestures."

resticking is achieved by maintaining a last position per sticky skeleton, a time-to-live (TTL), and an active flag. If a sticky skeleton isn't found on a current skeleton frame, then its active flag is set to false. Once the active flag on a sticky skeleton is false, its TTL decrements every frame until it's either found or the TTL reaches zero. The sticky skeleton is discarded if the TTL reaches zero, and then a sticky gesture is required. If the active flag is false and the TTL is greater than zero, then the last known position of the sticky skeleton is compared to the positions of all of the skeletons in the scene. A position-only comparison doesn't require fully tracked skeletons, and therefore all skeletons in the scene may be compared to the last position of the lost sticky skeleton in each frame. If the position of a skeleton in the scene is near the last known position of the lost sticky skeleton, that skeleton becomes sticky and the active flag is set to true.

Bringing it all together presented the largest challenge. Monitoring learners and determining purposeful actions executed correctly, incorrectly, or out of order in conjunction with physical objects using only the Kinect is difficult but achievable. To capture the interaction between users and their environment zones, watchers and observable actions were created.

- Environmental zones are 2D or 3D and represent an area in the user space. Zones exist for both skeleton joints and tracked colored objects. They report whether the skeleton joint or tracked color exists within the zone and for how long, continuous duration, and total time. With zones, AIMS is able to discern where the users, or objects, are relative to each other.
- Watchers run in parallel and perform checks on the scene to assess which actions, if any, are taking place. Multiple watchers might exist to assess a single action, depending on how many checks an action might need. For instance, during the performance of chest compressions, watchers exist just to ensure that the learner's arms are locked and not bent. These watchers measure the distance between the wrists, the angle of their individual arms from their shoulders to their hands, and the distance between their elbows. On the other hand, measuring that the user is positioned directly over the mannequin during compressions only takes a single watcher, a level of assessment never before present in medical simulation systems.
- Observable actions provide a succinct means of describing the current state during the performance of a procedure. As the user performs actions, they're marked as either correct or incorrect. If the watchers within a module observe an action properly performed, the observable action with those checks is marked as correct. Similarly, if the watchers observe an action improperly performed, the associated observable action is marked as incorrect.

Using off-the-shelf gaming technology allows us now to measure the location and orientation of instruments and joints in space with approximately 1/10-mm accuracy, after all the aforementioned challenges were solved and implemented. As the target platform is a midrange Windows 7 laptop, the resulting overall system is relatively affordable.

Finally, the UI of AIMS was designed to provide a similar look and feel to other software utilizing Kinect. The novel part of AIMS is AIMI. AIMI guides a learner through the experience. AIMI's speech is synthesized with Microsoft speech packs and doesn't rely on prerecorded audio clips. When performing a module, the learner can ask for help by simply saying, "AIMI help," and AIMI will respond with instructions for the current task within the module. The learner can also say, "AIMI video," and a video will be displayed over the current lesson showing how to perform the current task with more thorough instructions. As AIMS progresses,

AIMI lifelike constructive feedback is gaining a larger role with the learners' experience. The learner should always have a clear understanding of where assistance, guidance, and feedback come from, to ensure a positive learning experience.

Application Examples of AIMS

AIMS currently includes four modules, which will be described in further detail when focusing on the conceptual challenges of developing a procedural mastery model. Figure 4 shows the options located in the main page for AIMS. When one of these modules is selected, the system provides the student with the context of the training module and its specific pass requirements.

We selected and developed the modules based on the community's needs, to further demonstrate the feasibility of procedural skill acquisition with the chosen technological approach.

- *Intubation.* Demonstrates the high accuracy of procedural evaluation and analysis. It also futher showcases the ability for AIMS and AIMI to train individuals' clinical procedural skills.
- *Vertical lift.* Observers learn lifting heavy objects. This trainer isn't exclusive to clinical experts. Organizations that employ personnel required to transport heavy materials safely (such as postal service and warehouse workers) can also benefit from this module.
- *Lateral transfer.* Supports team training of moving a patient from a stretcher to a bed. Although the current version of the Microsoft Kinect camera allows tracking of two individuals, the next generation and its application allows tracking of up to six individuals.

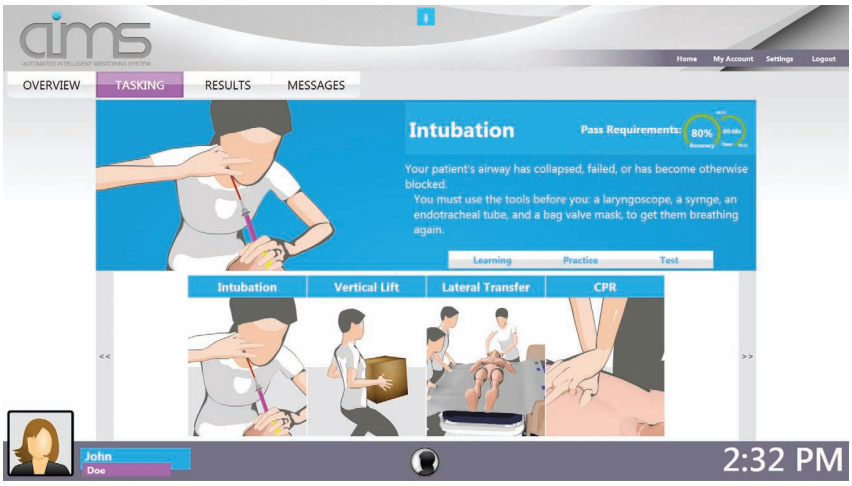

Figure 4. AIMS tasking screen. When a module is selected, the system provides the student with the context of the training module and its specific pass requirements.

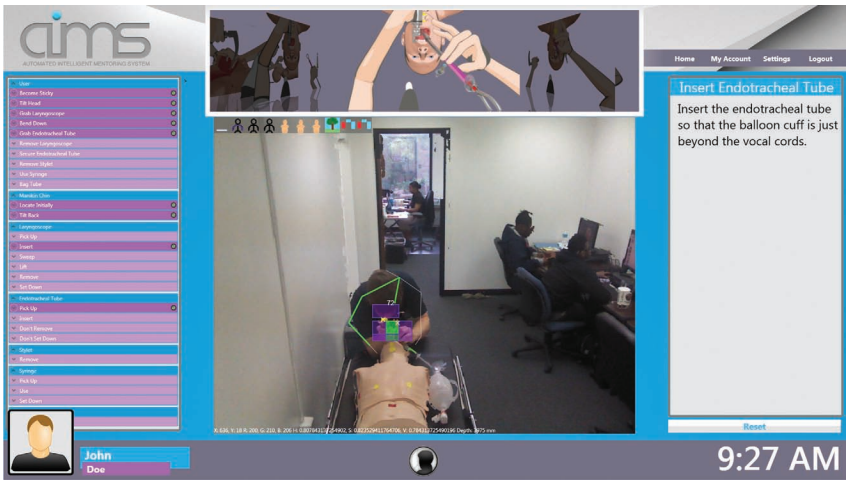

Figure 5. Screenshot of intubation: Inserting the breathing tube.

- *Cardiopulmonary resuscitation*. This training module was developed in support of "mass applications" such as CPR training in schools, business organizations, and nonprofit organization like the YMCA. According to the American Heart Association,[3] nearly 383,000 out-of-hospital sudden cardiac arrests occur annually, and 88 percent of cardiac arrests occur at home. A study published in *Circulation* shows that people who are bystanders often don't act due to the lack of confidence,[4] and just watching a video helps, but how much more confident will people be when they were trained with a system that provides professional feedback?

The following screenshots depicted in Figures 5, 6, and 7 show AIMS in action. The interface's screen elements are purposely identical, to provide a similar look and feel for the student, thereby ensuring that information within the same category is shown at the same location.

- The individual phases are shown on the left side of the screen. In learning mode, AIMI guides the student through all phases, explaining at the beginning of each phase what to do. In training mode, the student can ask AIMI for help at any time during the exercise. AIMI can also give advice if certain mistakes

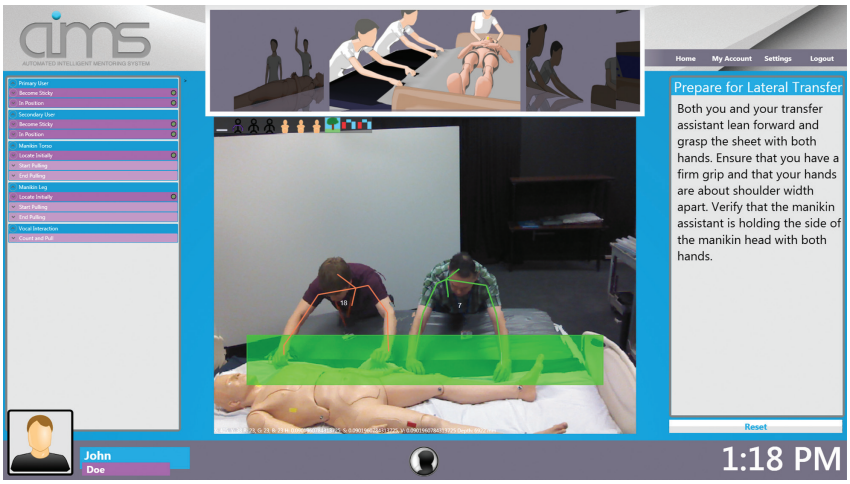

Figure 6. Screenshot of lateral transfer: two team members safely move a patient from the bed to a stretcher.

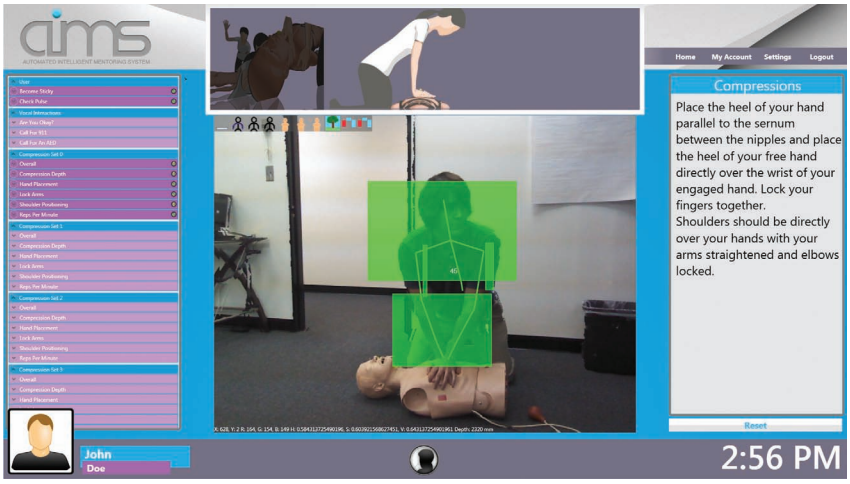

Figure 7. Screenshot of cardiopulmonary resuscitation (CPR) training.

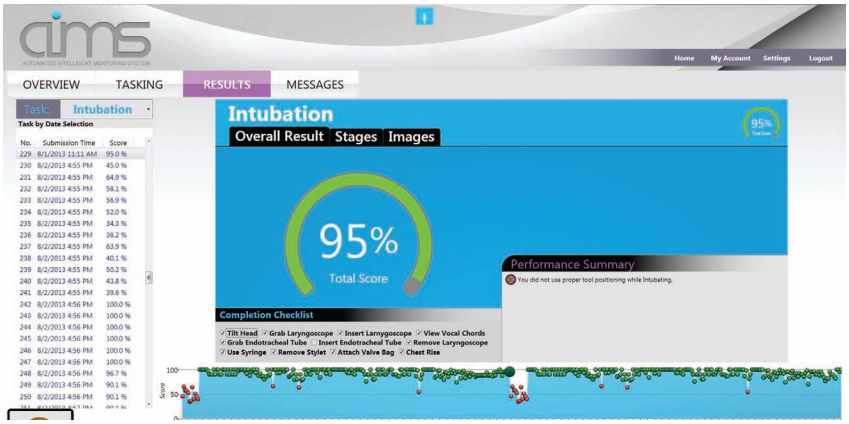

Figure 8. Overall results display for several tests: The display shows a histogram of scores observed for the trained individual or group allowing to recognize trends, in particular potential shortcomings and gaps that need to be closed to improve the training.

are observed during training. The final mode is the performance assessment mode. In this mode, an instructor could assess performance to grant the learner's certification or recertification. In this specific mode, no feedback is provided until the end of the procedure.

- At the top of the screen, the current required activity is shown using a cartoon/avatar figure.
- Additional feedback is provided in dialog/chat form on the right. This text becomes part of the protocol and can be used for additional user feedback after the tests.
- The center of the screen is used to provide visual feedback to the student. It shows the video as captured by the Kinect camera, augmented by color-coded displays of recognized zones important for the current activity.

The design of AIMS includes the storage of user-specific data that can be integrated into a learning management system. This also allows for the performance tracking of each individual, as well as an entire group's performance over time. The last screenshot (see Figure 8) shows a possible evaluation screen, listing the various available data on the left, displaying the last evaluation in the center, and providing a histogram using the scores of individual test results at the bottom. This presentation has been designed to provide instructors with visual clues about the learner's success rates and their performance challenges—for example, any capability gaps that must be addressed in more detail.

In addition, stage images that include more detailed test results are captured and stored, which can be evaluated using aggregation and visualization algorithms.

Advantages of AIMS

In an evaluation report provided to the Center for Innovative Technology,[5] the following advantages were found:

- AIMS lets students train for clinical procedural skills by enforcing standardized, positive learning experiences without the need of a clinical expert in this procedure to be present.
- Students can practice a procedure as often as they need to, until they attain the required skill level. This practice can be conducted ad hoc wherever the AIMS system is available, including after hours.
- AIMS provides exact measurements of procedural accuracy within allowed tolerance levels. Observation by an expert is replaced by totally unbiased measurements and comparison with the required activities.

We should note that AIMS hasn't been developed to replace clinical experts, but to relieve them from the burden of time removed from the clinical environment, handling time-consuming individual instruction, providing objective skill assessment and other activities that can easily be supported by computed functionality. This is a complementary approach to the human subject matter expert that takes full advantage of the utility of simulation in medical education.[6]

Use and Acceptance of AIMS

The validation of AIMS is an ongoing process, but initial tests show very promising results. As a part of one of the application domains of the current AIMS product lines in development, the AIMS CPR training module was taken for preliminary product testing and evaluations to the Start Norfolk event that involves engineers, entrepreneurs, and investors, as well as business developers. This event is focused on bringing together individuals with the ultimate goal of building and creating a startup company over the weekend. The AIMS CPR training module was used as an example to show participants what practical applications of hands-free gaming innovations can produce. This led to engaged participation with the CPR product and eagerness to test its various features. The numbers of engagements were insufficient to claim statistical relevance. There was no control of who in the group participated and no pedigree data was collected. Before the CPR training, each participant was asked, "If you were to encounter an individual on the street, would you feel confident in performing CPR?" All participants received a short introduction to AIMS. AIMS then measured and displayed their performance. No individual was required go through more than one repetition. After completing the CPR training with AIMS, each participant was asked "After having that training experience, are you now confident in performing CPR if you were to encounter an individual on the street?" The observed trend was as expected:

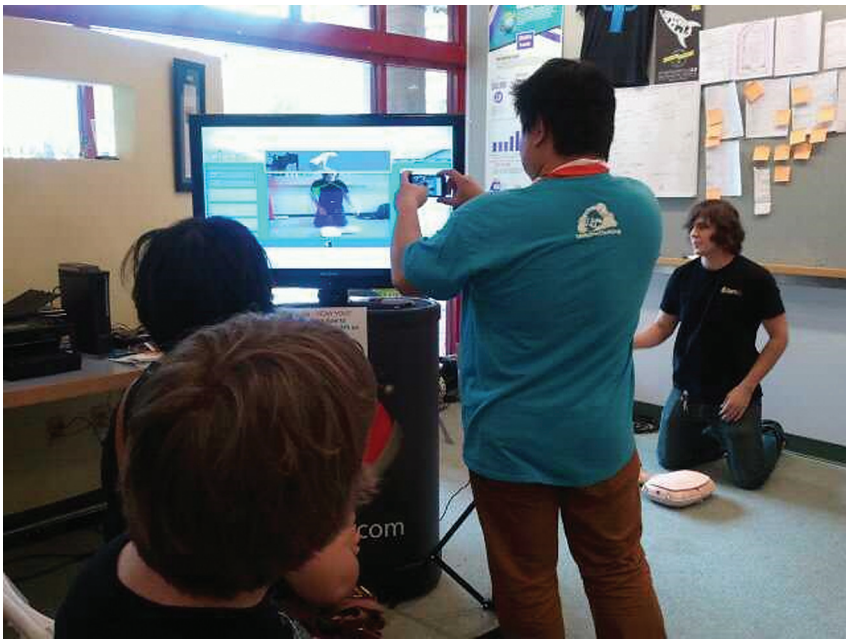

Figure 9. Interaction with AIMS during the Start Norfolk event in Virginia.

- One third of the participants felt confident *before the test*, while two thirds answered that they felt confident enough in performing CPR *after the test*.
- One third of the originally confident people felt non-confident in their CPR abilities after the test, but felt compelled to retake the test. Sixty percent of those skeptical of their abilities became confident that they can perform CPR after the short training and evaluation.

As the lack of confidence has been identified as one of the main reasons that people don't perform CPR when it's needed in the already-addressed study,[4] this preliminary data hints towards a successful application of AIMS. It engaged all participants, and some even returned with friends to introduce them to the technology.

The team also conducted some initial surveys at EVMS to collect feedback from students and faculty regarding the usefulness of AIMS to practice clinical procedural skills. The majority of students asked so far are in favor of having the opportunity to practice with AIMS, in particular when they can use this help within their time constraints.

Whether students utilize comparable games for recreation doesn't seem to be a factor, but more evaluations are needed to provide a statistically sound foundation.

The results of the currently ongoing acceptance tests and validation efforts, which are being conducted on a broader scale, focusing on engaging healthcare and training providers who weren't part of the development team, will be the subject of a future publication.

Future Development

The obvious future effort is the development of additional modules. As shown within the current AIMS product, the acquisition of procedural skills of individuals as well as small teams can be supported by computer-based simulation solutions. Therefore, which procedures we support is only confined by the imagination of users, developers, and hardware limitations.

One of these realized hardware limitations is the accuracy currently provided when it comes to the support of microscale procedural skills. Although the accuracy of the Kinect is sufficient for many fine-movement modules, a much higher accuracy is needed for special domains. To be able to support these fields as well, hybrid sensor technology is needed. Tests are underway to understand the feasibility of combining the Kinect technology with the Myo gesture control armband by Thalmic Labs (see www.thalmic.com/en/myo) and the Leap Motion Controllers (www.leapmotion.com). While MYO measures muscle activity in the forearm, Leap is a high-accuracy motion sensors that tracks all 10 fingers up to 1/100th of a millimeter. Both sensors increase accuracy significantly, but the data delivery methods are different in each system. If a multiresolution approach on the simulation side is needed to support a hybrid multisensor approach that's going to be implemented, ongoing research will be required.

The use of serious games for medical education is becoming a more frequent occurrence in modern medical training scenarios. However, most of these applications are standalone applications. The objective is to ultimately compose a realistic and emergent environment for the learner, in which the various components are no longer standalone, but are integrated by an interoperability framework that taps into all elements (for example, the serious game is used to set the context for a situation in which CPR is needed). The time the student needs to realize what to do in this situation, as well as the student's procedural skills in conducting CPR on the mannequin, are fluent elements of one big scenario, in which a variety of interoperable simulators and sensors support a superior educational experience.

Using creativity and computational expertise, the target system remained very affordable. Besides resulting in a potentially life-saving technology, the lessons learned for computer experts comprise the observation that best solutions aren't always connected with more computing power. Using color-coded instruments instead of shape-recognizing, high-performance computing solutions, for example, kept the overall system simple and effective. Introducing "sticky gestures" to identify the learner to be observed proved to be a highly effective trick. Adding joint history as a constraint resulted in the exclusion of many options that no longer had to be computationally evaluated. Many of these simple solutions were first recognized by non-computer-specialist team members. Overall, the project was a great experience for all team members.

The resulting AIMS system measures and analyzes the movements of users in relation to training devices, instruments, other individuals, and environmental elements to assess and measure human performance against a master model while conducting a clinical procedure. With great precision in the measurement of human performance, AIMS offers objective feedback and detailed comparisons established by the data capture of standardized expert performance models. As such, it introduces a new capability to the use of serious gaming technology for medical education and skills training.[7]

Over the course of two separate studies, learners introduced to AIMS in both the clinical and non-clinical environment were observed to show an 80 percent improvement in procedural performance and increased learner confidence. Learners consisted of both recreational gamers and non-gamers, of whom a majority found the interface easy to understand and results clearly expressed. These initial studies tracking performance metrics and user experience were comprised of both the endotracheal intubation and CPR modules, with no physical clinical instructor in the loop.

Unlike current simulation training models that require on-site instructors and often one-on-one interaction between the learner and instructor, this technology accomplishes the same outcome in a more cost-effective manner. This is achieved by leveraging and combining the AIMS software system with existing simulation training equipment, off-the-shelf computers, and motion-capture systems. It

provides comprehensive, real-time interactive instruction, including active audio and visual cues and dynamic feedback to users. As such, it could help decrease the cost of medical education—in particular, the teaching and training of critical clinical procedures—and lead to superior quality, effectiveness, and efficiency of the learner's education.

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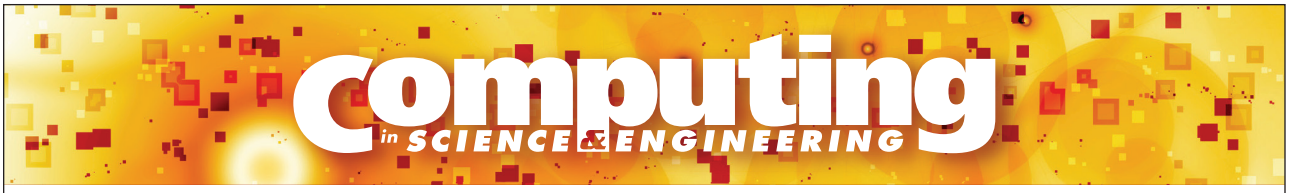

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