Immersidata Analysis: Four Case Studies

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Four real-world case studies demonstrate the effectiveness of using *immersidata*—the normally untapped data from interchanges between users and immersive 3D environments such as computer games and virtual reality—to help understand user behavior and experiences.

Some years ago, we realized that the moment-to-moment interchanges of cues and responses between humans and technological devices, products, and digital media teem with untapped information. So, rather than discarding them, we could store, analyze, and use the transcripts of data streams from human-technology interchanges.

To demonstrate our supposition, our initial work has focused on immersive environments such as virtual reality and computer games in which a user interacts with people, objects, places, and databases. We monitor users through various video, optical, and magnetic positional and sensory tracking devices attached to various parts of the user's body as well as to a keyboard and mouse.

To represent the data acquired from users' interactions with immersive environments, we coined the term *immersidata*.[1] Immersidata analysis is the practice of automatically searching, processing, and manipulating the data collected from user interactions with immersive environments to understand or predict behaviors and intentions in the context of the immersive application.

After several years of studying various immersive applications and immersidata sets, we developed An Immersidata Management System, a framework consisting of four connected modules.[2] AIMS treats immersidata as several multidimensional sensor data streams and addresses the challenges involved in its acquisition, storage, query, and analysis.

To illustrate immersidata's importance, we report four real-world case studies in the medical and educational domains. We show that immersidata can be as revealing, if not more so, as the results obtained with other experimental monitoring and observation, data collection, and analysis techniques. Our purpose, however, isn't to replace these techniques or the human experimenters, but to provide a complementary approach that allows for data that would normally be lost to be captured and analyzed.

These four case studies represent our preliminary work to showcase immersidata's usefulness. This collection of case studies demonstrates that a general data architecture for acquisition, query, and analysis of immersidata can be beneficial to many fields, regardless of their focused applications.

ATTENTION DEFICIT HYPERACTIVITY DISORDER

Collaborating with a large interdisciplinary team, we found that children thought to have attention deficit hyperactivity disorder (ADHD) could be diagnosed more accurately by studying immersidata in the form of signals coming from hand-, leg-, and head-tracking devices they wore while exploring a virtual classroom

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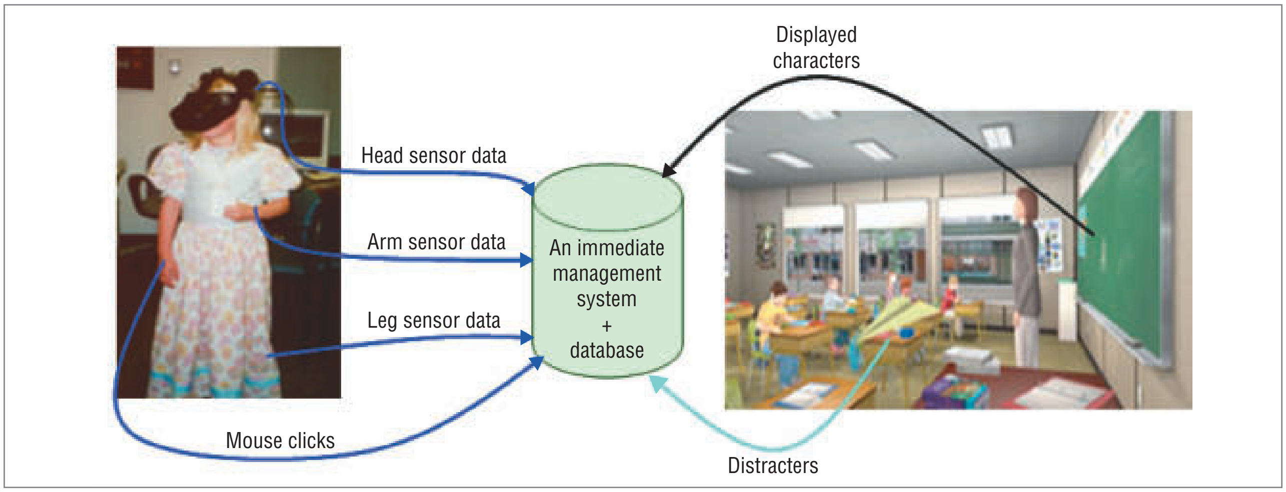


Figure 1. Attention deficit hyperactivity disorder (ADHD) experiment arrangement with immersidata database architecture.

environment.[3-5] We could answer important questions by analyzing the immersidata in conjunction with the situational and cognitive performance data gathered in the virtual classroom environment. For example, what is the average hand movement speed? Was there a distraction in the environment when the child gave the wrong answer to question x at time t? Was the child looking toward a distraction? If so, for how long was the child looking at the distraction?

In one of our experiments, subjects wore a head-mounted display (HMD) and held a 3D mouse with a button. We displayed the letters of the alphabet on the virtual classroom blackboard, and subjects were to click the button whenever the letter "A" followed by an "X" appeared. In addition, we periodically introduced distractions such as a paper airplane flying from one side of the classroom to the other and virtual people entering the classroom.

As Figure 1 shows, during experimental sessions, we gathered the x, y, and z position information and pitch, roll, and yaw rotation information from three Ascension Flock of Birds trackers, one attached to the HMD, another to the arm, and the third to the leg, with a sampling rate of about 10 Hz. The collected data also included the letters shown on the blackboard. Each session lasted about 618 seconds, and 400 letters were presented during the session. Each session has 20 "correct" letter sequences—"A" followed by "X." Finally, we collected subjects' button clicks.

We conducted preliminary experiments with 21 subjects (10 ADHD subjects and 11 non-ADHD subjects). Figure 2 shows examples of two subjects' movements during the experimental sessions. Subjects with ADHD tended to move more than non-ADHD children during study sessions and this movement increased during testing in a distraction-rich session.

Based on this observation, we tried to identify ADHD and non-ADHD subjects using the information from the three Flock of Birds trackers. We represented each session as an $M \times 18$ matrix, where M depends on the session duration and 18 is the total number of sensors for the three trackers. We computed the sensor-wise standard deviation and hence represent each session as 18 values.

Our initial experiment used support vector machines to perform the classification and radial basis function (RBF) kernels and leave-one-out cross-validation. It produced a 95.238 percent accuracy rate for ADHD/non-ADHD classification. That is, we correctly identified 20 out of 21 subjects (on the average based on leave-one-out cross-validation) as ADHD or non-ADHD.

This case study demonstrated that immersidata analysis can provide useful information for improving the identification of ADHD. Future research will investigate how using more data sets can further improve the classification accuracy.

NEUROREHABILITATION

Concurring with a team of our interdisciplinary collaborators from neurorehabilitation,[6] we found that sampled kinematics immersidata provides rich information for studying the functional behavior of poststroke patients. This approach is in contrast to traditional approaches in which specialized staff, such as physical therapists, assess the upper and lower extremity behaviors of poststroke patients by analyzing videotaped images of them performing certain tasks as well as their responses to standard pre- and posttask questionnaires.

In our preliminary studies, three healthy subjects used as controls (C) and two poststroke patients (S) performed a continuous reach-grasp-place rehabilitation task five times (25 trials in total). Six-degree-of-freedom (6 DOF) electromagnetic Ascension Minibird trackers traced the subjects' motor activity as they performed the rehabilitation task. We attached the trackers to the subjects' upper extremity and limbs: index nail, thumbnail, dorsal hand, distal dorsal forearm, lateral mid-upper arm, and posterior neck. We sampled the six

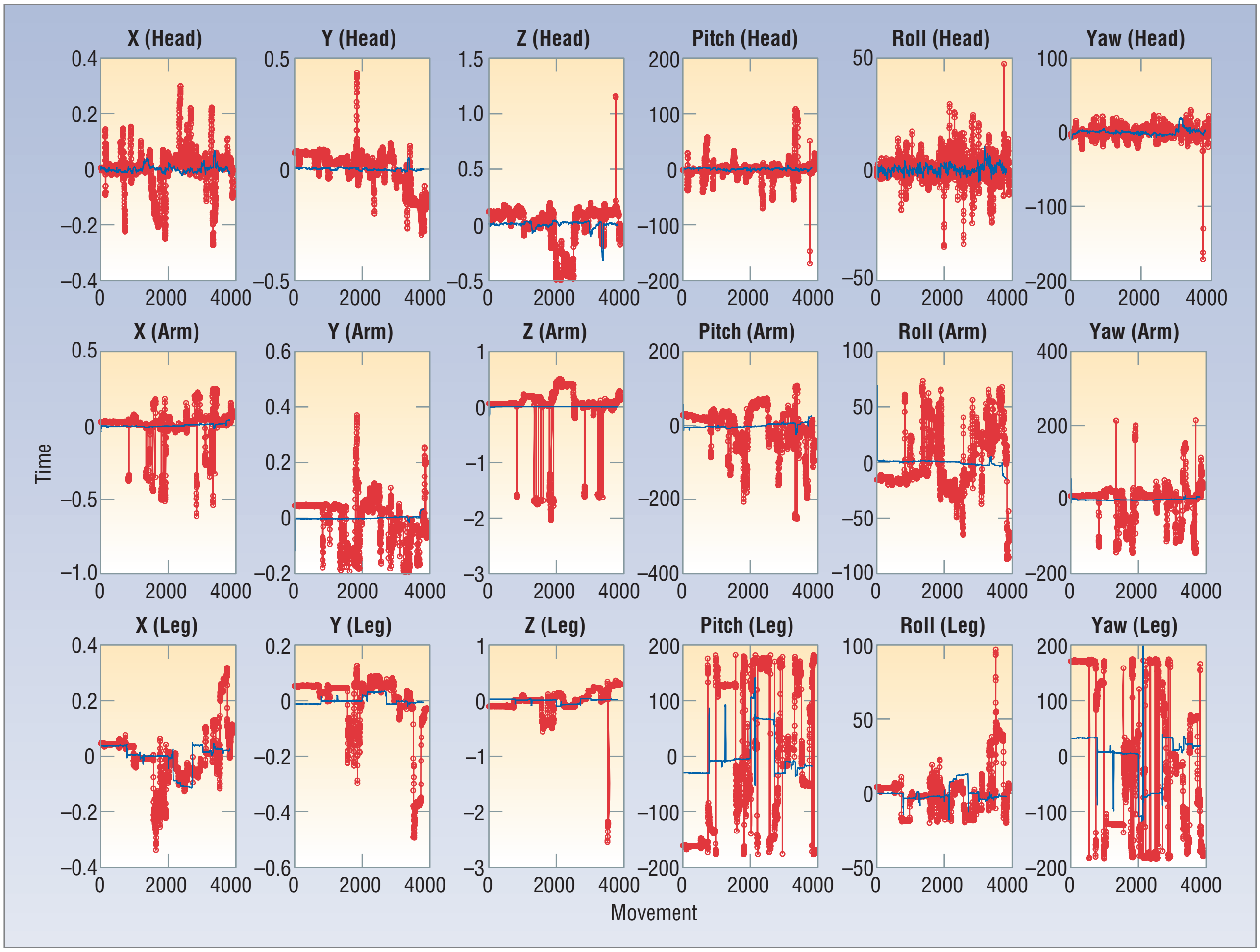


Figure 2. Children's head, arm, and leg movements during two sample sessions. ADHD subjects appear in red, and non-ADHD in blue. The sampling rate was around 10 Hz, so the measure for the x-axis is one-tenth of a second. For the y-axis, the measure is inches for X, Y, and Z, and degree from –180 to 180 for pitch, roll, and yaw.

sensors' raw data—*x*, *y*, and *z* coordinates for position and orientation—at 120 Hz.

The data set collected for our analysis included the subjects' forearm movement, which was captured by 11 variables (from 36 raw features—that is, 6 DOF from six sensors): the wrist sensor *x*, *y*, and *z* coordinates, and the derived variables representing the aperture, elbow flexion/extension, forearm supination/pronation, wrist flexion/extension, wrist radial/ulnar deviation, shoulder flexion/extension, shoulder horizontal abduction/adduction, and shoulder internal/external rotation. In addition, an event marker recorded each trial's start and end points.

We represented each session as a matrix in which rows contain the 11 variables and a time stamp for each of the corresponding five trials.

We used principal component analysis to graphically visualize the associations or correlations among sessions and thus to understand the differences between healthy subjects and poststroke patients in terms of their forearm functional behavior. We applied principal component analysis to the data matrix representing all 25 sessions row-wise, where each row is a vectorized covariance matrix of session data. By projecting all sessions onto the subspace spanned by the first and second principal components, we obtained a compact 2D overview, which maintains the most variability underlying the data among all possible linearly transformed 2D representations.

The *x* and *y* chart axes in Figure 3 represent the first and second principal components, respectively. In addition, we can easily determine a decision boundary separating poststroke patients' (*S*) from healthy subjects' (*C*) sessions (as illustrated by the diagonal line) in this reduced 2D visualization. This demonstrates that more variations exist across subjects than within a subject, implying that a certain behavior pattern might be associated with a subject. Furthermore, the healthy subjects' five trial sessions are close together, showing a more consistent performance than poststroke patients' performance, which is sparsely distributed.

In future work, we intend to collect more data in an attempt to validate our visualization method and inves-

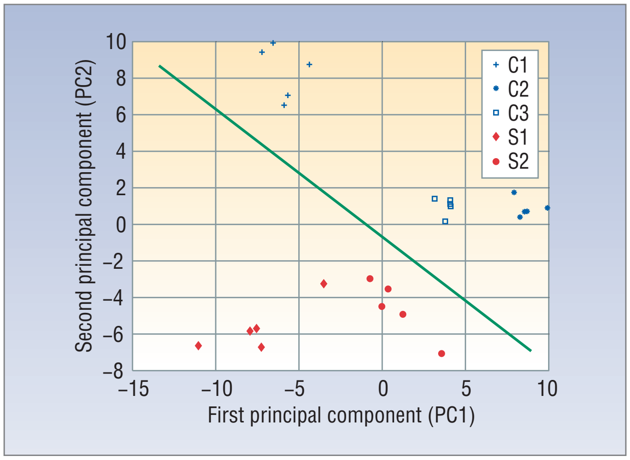


Figure 3. Projection of poststroke patients' (S) and healthy subjects' (C) sessions onto the subspace spanned by the first and second principal components.

tigate whether we can use this method as an analytical tool to reliably and accurately capture improvements in patients' forearm movement as they repeat the rehabilitation task.

STUDENT ASSESSMENT IN COMPUTER GAMES

In the interdisciplinary 2020Classroom project, we've been involved in developing and implementing a 3D educational immersive "serious game" environment. The game lets students interact, explore, and learn the physiological and physical processes of human organs. We used immersidata representing students' experiences and behavior in this game environment to detect problematic design aspects and indicate students' learning outcomes.[7-9]

To guarantee seamless interaction between the game and query engines, we customized database schema and storage subsystems in C++ using Oracle, open database connectivity (ODBC), and the DB2 CLI Template Library (http://otl.sourceforge.net) for the game. Figure 4 is a schematic of the architecture for collecting immersidata. It provides a continuous and unobtrusive approach to capture and store students' movements (directional and angular) and events occurring as a result of interactions within the game environment.

We collected and stored four types of data:

- demographic data such as gender, age, and degree major;
- answers to questionnaires, such as a student's knowledge about human physiology;
- game object geometry; and
- an immersidata stream generated as a result of students' interactions with the game engine.

The conventional relational model was sufficient to describe the demographic and questionnaire data, but we used the object-relational model, implemented in

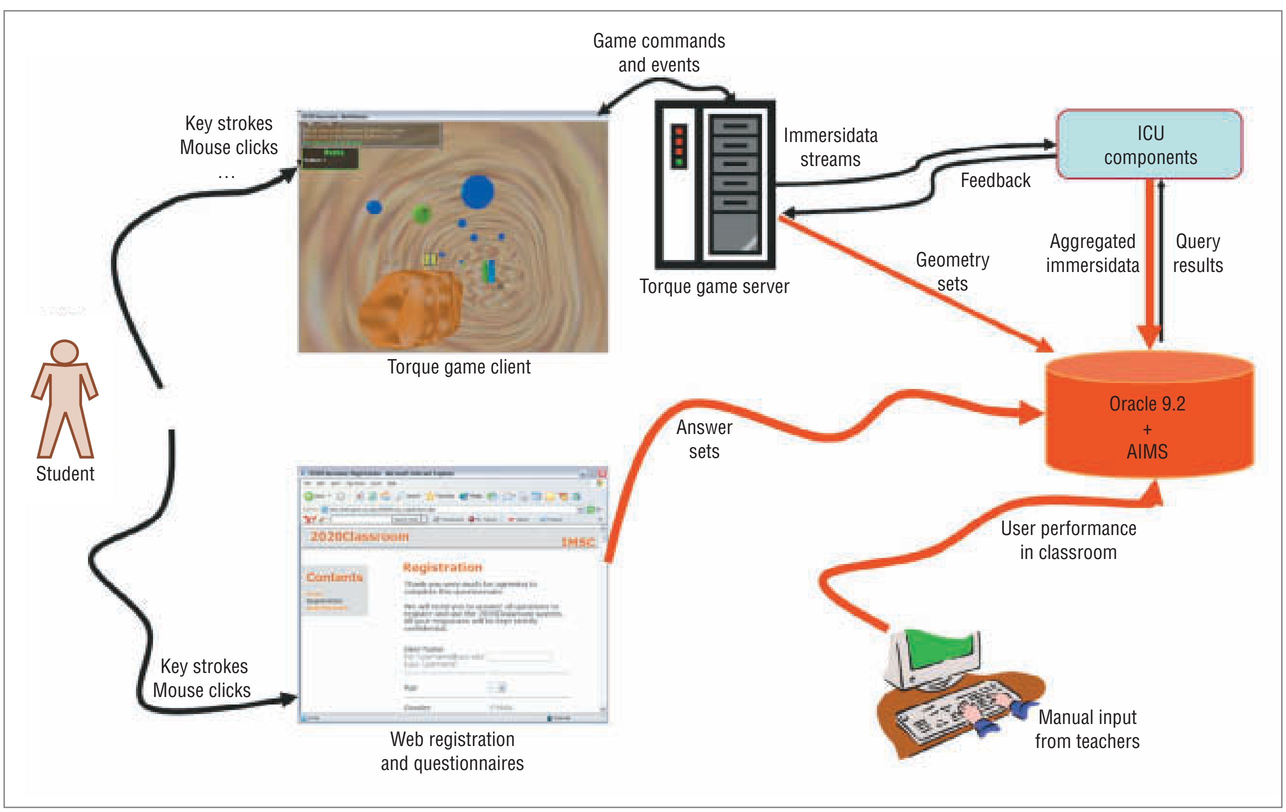


Figure 4. Schematic of the architecture for collecting immersidata in the 2020Classroom project.

Oracle 9i with spatial and temporal cartridges, to describe the game object geometry.

The immersidata streams include

- The stream of events initiated by users and the game engine. An event stream tuple is in the form: [*User ID, event ID, trigger, status, object, (x, y, z), (rx, ry, rz), view angle, time*]. For example, the tuple [339, place, selection, no organ selected, Muscles, (305.943, 296.373, 225.375), (0, 0, 1), 3.65967, 2004/04/30 12:48:16] represents user 339, who failed to place an object on Muscles because no organ was selected.
- Player position data (including the actual position, view direction, and body rotation) in the game space. The position data schema is: [*User ID, position (x, y, z), viewpoint (rx, ry, rz), view angle, time*].

We present two approaches for analyzing the collected immersidata.

First, we hypothesized that we could use zero or near-zero immersidata (directional and angular movement and events) generated from immersive environments to identify interruptions or breaks in users' experience caused by problematic design. We validated our hypothesis by identifying moments when near-zero immersidata occurred in a study with 10 subjects, and then viewing these points or durations in video recordings of the study sessions. We identified many problematic design aspects and used this information to inform redesign. This cost-effective approach considerably reduces the time game evaluators and developers spend analyzing hours of study material captured on video.

Our second approach aims to expedite the analysis of the immersidata in the first approach. Our Immersidata Analysis (ISIS) application indexes breaks within video clips of students' gaming sessions. For example, Figure 5 shows the ISIS graphical user interface displaying a break in which a subject doesn't know what to do next in the game.

Currently, ISIS supports four queries that are effective for analyzing and improving the game environment:

- *Find all break points*—moments in which the subject makes no movement and no events occur for a specific period. Breaks provide clues to causes of game play interruptions.

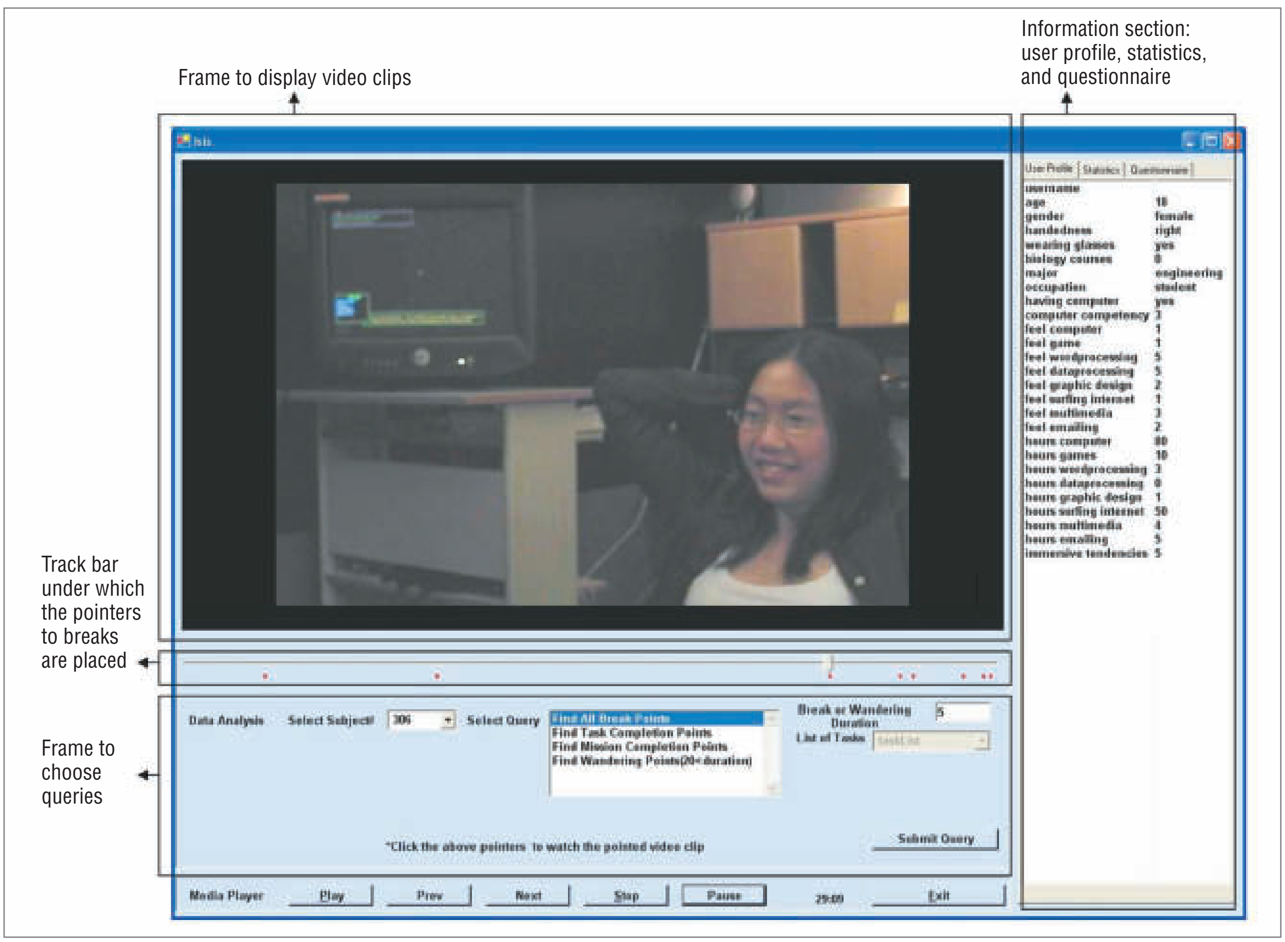
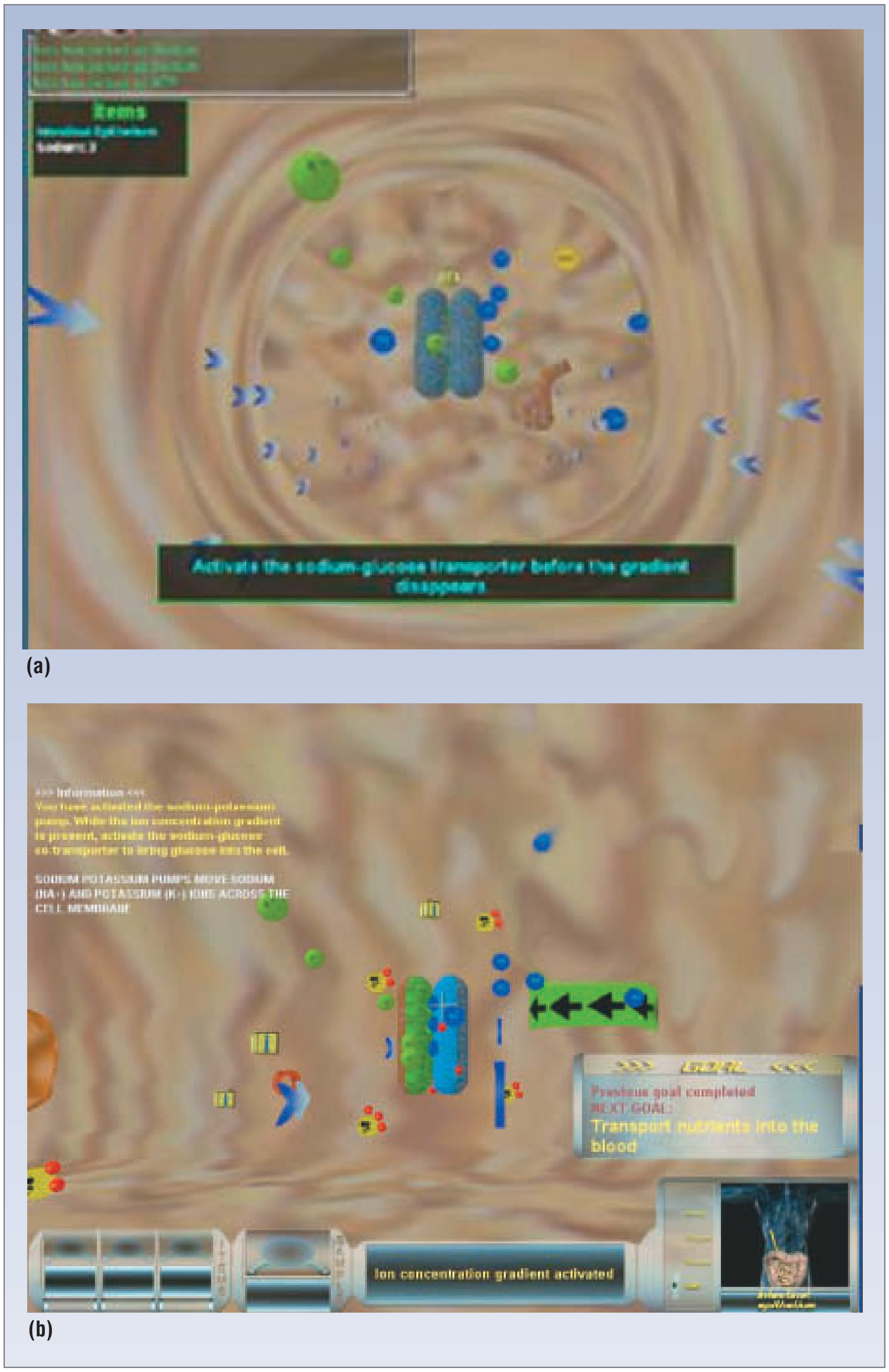


Figure 5. The Immersidata Analysis (ISIS) graphical user interface. The indexed video clip shows a break in which a subject doesn't know what to do next in the game, potentially indicating a design problem.



(a)

(b)

Figure 6. Resolving design problems: (a) an earlier version of the educational serious game environment and (b) a later version with the design problems resolved.

- *Find wandering points*—periods during which the subject moves but doesn't make any movement for a specific period. Subjects might wander, for example, when they're uncertain of the next movement to make to accomplish the task.
- *Find task completion points*—the moment when a subject finishes a specific task.
- *Find mission completion points*—the moment when a subject finishes all the given tasks.

In future work, we plan to add more functionality to ISIS to let it identify problematic game design that can interrupt subjects' learning or game play. For example, one useful query would be to recognize subjects' repeated actions that aren't intentionally designed game tasks.

Using these two techniques (that is, identifying near-zero immersidata and ISIS) facilitates the analysis of subjects' experience and behavior with and within a game environment, identifies problematic design occurring momentarily or in situational and episodic events, and informs design improvements. Table 1, for example, lists the design problems that we identified through breaks in an earlier version of the scene, "Sodium-Potassium Pump," and a later version with the design problems resolved. Figure 6 shows the original and revised versions of the game.

In future work, we'll apply these techniques to identify interruptions or breaks in other technological devices, products, and digital media in real-world settings such as work, leisure activities, and the home environment.

MENTAL ROTATION

One of several human visuospatial abilities, mental rotation (MR) is a dynamic imagery process involving "turning something over in one's mind."[9] Automobile driving, sports activities, using a map, and other everyday life situations in which the user must visualize a physical object's movement and ultimate placement in 3D space rely on this ability to turn over or manipulate objects mentally.

Roger Shepard and Jacqueline Metzler began initial MR investigations about 30 years ago.[10] They presented pairs of 2D perspective drawings to subjects and asked them whether the 3D objects they portrayed were the same or different.

Our preliminary MR study required subjects to manipulate and superimpose block configurations within an

Table 1. Design problems and their solutions.

Problems	Solutions
The subjects lost track of where they were and became disoriented inside the human organs.	A map of the human body indicating the user's location is displayed at all times in the bottom right-hand side of the screen.
The tasks weren't explicitly explained, and subjects were often unaware of the next task in the mission.	A sliding instruction box appears at the bottom right-hand side of the screen for a short duration to remind subjects of their goals.
The 3D models of human organs and tissues weren't intuitive enough, confusing subjects. For example, subjects had no idea that they could pass through an opaque membrane wall.	A revolving green cylinder with black arrows in the membrane wall helps subjects understand that they may pass through the membrane wall.

immersive environment. We used an immersive stereo environment to assess visuospatial abilities to allow greater control and description of 3D stimuli along with more precise response measurement. We expected this to support a more accurate characterization of the cognitive processes involved in functional visuospatial skills than standard 2D paper-and-pencil measures afford.

The Mental Rotation within Immersive Environment (MRIE) system presents a target stimulus consisting of a specific configuration of 3D blocks within an immersive environment. The stimuli appear as 3D objects floating in 3D space. After presenting a target stimulus, the system presents the participant with the same set of blocks (control stimulus) to rotate to the target's position and orientation and then superimpose on it.

Participants wear a 5DT Data Glove with a Flock of Birds tracker attached to it and CrystalEyes shutter glasses for 3D stereo view. Participants manipulate the control object by making a fist, mimicking the behavior of holding the control object, and then moving their hand.

The system imparts the hand's motion on the control object only when the participant is making a fist with the glove. A "correct" feedback tone signals successful superimposition of the control and target objects, and the next trial begins. A new control object appears attached to the user's hand, and the new target appears a short distance away.

We conducted an experiment with MRIE in which we tested 20 subjects (10 men and 10 women) between the ages of 20 and 37. Each participant's experimental session had 24 trials. Participants wore the 5DT Data Glove-16, which has 14 sensors that measure values such as angles between joints and abduction between fingers. The Ascension Flock of Birds tracker attached to the glove generates six values: the position information (x, y, and z) and the rotation information on each axis (pitch, roll, and yaw). Hence, at each time stamp, we got 20 values, with a sample rate of about 120 Hz. As a whole, the system stores 2,400 (20×120) values per second.

Men perform significantly better than women in 2D paper-and-pencil MR tests, indicating that gender differences could affect the ability to manipulate and rotate 3D objects.[9] Hence, using the data set from our MRIE experiment, we performed male/female classification with support vector machines. We divided each experimental session for a subject into 24 segments, each representing a trial. We grouped all of the segments for each trial together—that is, we grouped and processed all the segments for the first trial together and repeated this process for the remaining trials.

We represent each segment in an $M \times 20$ matrix, where M is different for different segments. Subjects don't finish a trial at the same time, thus trials have different durations. However, the support vector machine inputs should be the same length. Hence, we first compute the correlation matrix of all the segments. This way, we can represent all the segments as 20×20 matrices.

Using RBF kernels and leave-one-out cross-validation for each group of segments, our initial experiment produced an average accuracy rate of 74.1 percent for male/female classification. To identify the performance patterns in the immersive environment, we intend to perform a more in-depth exploration of this data and conduct more comprehensive experiments in the future.

Used in conjunction with other existing experimental monitoring and observation, data collection and analysis techniques help promote a greater insight to user behavior and experience. In ongoing and future work, we're applying the techniques described herein to help us understand the behavior and experiences of users when they're immersed in activities involving interchanges with technological devices, products, and digital media at work, in the home, and in leisure environments.

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