Two gesture recognition systems for immersive math education of the Deaf

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ABSTRACT

The general goal of our research is the creation of a natural and intuitive interface for navigation, interaction, and input/recognition of American Sign Language (ASL) math signs in immersive Virtual Environments (VE) for the Deaf. The specific objective of this work is the development of two new gesture recognition systems for SMILE™, an immersive learning game that employs a fantasy 3D virtual environment to engage deaf children in math-based educational tasks. Presently, SMILE includes standard VR interaction devices such as a 6DOF wand, a pair of pinch gloves, and a dance platform. In this paper we show a significant improvement of the application by proposing two new gesture control mechanisms: system (1) is based entirely on hand gestures and makes use of a pair of 18-sensor data gloves, system (2) is based on hand and body gestures and makes use of a pair of data gloves and a motion tracking system. Both interfaces support first-person motion control, object selection and manipulation, and real-time input/ recognition of ASL numbers zero to twenty. Although the systems described in the paper rely on high-end, expensive hardware, they can be considered a first step toward the realization of an effective immersive sign language interface.

Categories and Subject Descriptors

K. Computing Milieux - K.3 [**Computers and Education**]: K.3.1 Computer Uses in Education - *Collaborative learning, Computer-assisted instruction (CAI), Computer-managed instruction (CMI).*

General Terms

Design, Human Factors.

Keywords

Sign language recognition, HCI, Virtual Environments, Deaf education

1. INTRODUCTION

Deaf education, and specifically math/science education, is a pressing national problem [1, 2]. To address the need to increase the abilities of young deaf children in math, we have recently created an immersive application (SMILE™) for learning of K-5 arithmetic concepts and related ASL signs [3, 4]. SMILE is an interactive virtual world comprised of an imaginary town populated by fantasy 3D avatars that communicate with the participant in written English and ASL. The user can explore the town, enter buildings, select and manipulate objects, construct new objects, and interact with the characters. In each building the participant learns specific math concepts by performing hands-on activities developed in collaboration with elementary school educators (including deaf educators), and in alignment with standard math curriculum. The application is designed for display on different systems: a stationary projection-based four-wall device, i.e., the Fakespace FLEX [5], a single screen immersive portable system [6], and low cost Fish Tank VR systems. Presently, children travel through the virtual world using a 6 DOF wand or a dance platform, and can grasp and release objects using the wand or a pair of pinch gloves. SMILE has been evaluated extensively by a panel of experts and by groups of target users (i.e., children ages 5-11). As a result of these evaluations several usability problems have been identified:

1. To date, SMILE user interfaces do not allow for input/recognition of ASL signs. Children answer the questions posed by the 3D signers by selecting numbers from a floating menu which appears when needed. This presents a problem if we consider that deaf children of deaf parents are likely to know the signs for the numbers but might not be familiar yet with the corresponding math symbols. In this case, the children should be able to enter the answer to a problem by forming the correct ASL hand shape, rather than by selecting the number symbol.

2. SMILE requires the user to perform concurrent tasks. For instance, in certain situations, children need to answer a math question while moving through the environment carrying an object. Currently, SMILE interaction mechanisms do not fully support simultaneous and consistent tasking.

3. Deaf children of hearing parents use the application not only to increase their math skills, but also to learn the correct signs for math terminology. While the children can observe the 3D characters perform the signs, they cannot test and get feedback on their signing skills since all interactive activities require responses in the form of math symbols.

In an effort to improve on the current implementation of the program, we propose two new user interfaces which allow for first person motion control, object selection and manipulation, and real-time input and recognition of ASL math signs. Interface (1) uses a pair of 18-sensors Immersion cybergloves [7] coupled

IMMERSCOM 2007, October 10-12, Verona, Italy

DOI 10.4108/ICST.IMMERSCOM2007.2081

with an Intersense wrist tracker [8], interface (2) uses the cybergloves and a Metamotion motion capture optical system [9]; recognition of hand gestures is performed by a pre-trained neural network.

In Section 2 of the paper we address problems related to immersive sign language interfaces and we present a review of recent approaches in sign language input and recognition. In Section 3 we describe the two new user interfaces, and in section 4 we discuss their merits and limitations, along with future work. Conclusive remarks are presented in section 5.

2. BACKGROUND

Existing data suggest that immersive VLEs offer significant, positive support for education in general [10] [11]. In regard to disabilities education, literature findings show that VR has many advantages over other teaching technologies because it can fulfill the majority of the learning requirements of students with disabilities [12]. Some of the most commonly encountered needs of people with learning impairments include: control over environment; self-pacing; repetition; ability to see or feel items and processes in concrete terms (difficulty with abstract concepts); safe and barrier-free scenarios for daily living tasks; and motivation [13]. However, in order to be effective, VLEs for the hearing impaired need to support sign language interfaces, i.e., ways of input, recognition, and display of signing gestures.

Though there has been significant progress in development of sign language input recognition systems, the majority of interactive applications for the deaf still make use of standard input devices. For instance, in the only two existing examples of immersive VLE for deaf/speech-impaired students (i.e., the Virtual Supermarket [14] and the VREAL project [15]) participants use mouse, keyboard and joystick to interact with the programs; real-time input and recognition of signs is not supported.

In this paper we improve on the state-of-the-art by presenting a first step toward the development of an intuitive gesture-based system for natural communication and interaction between deaf users and immersive virtual environments.

1.1 State-of-the-art in sign language input and recognition

Sign language input and recognition has been an active area of research during the past decade. Currently, there are two main approaches to gesture input: direct-device and vision-based input [16-18]. The direct-device approach uses a number of commercially available instrumented gloves, flexion sensors, body trackers, etc. as input to gesture recognition [19]. Some advantages of direct devices, such as data gloves, include: direct measurement of hand and finger parameters (i.e., joint angles, wrist rotation and 3D spatial information), data input at a high sample frequency, and no line-of-sign occlusion problems. Disadvantages include: reduced user's range of motion and comfort, and high cost of accurate systems (i.e., gloves with a high number of sensors –18 or 22–).

Vision based approaches use one or more video cameras to capture images of the hands and interpret them to produce visual features that can be used to recognize gestures. The main advantage of vision-based systems is that they allow the users to remain unencumbered. Main disadvantages include: high cost, complex computation requirements in order to extract usable information, line-of sign occlusion problems, and sensitivity to lighting conditions.

Recently, researchers have started to develop gesture input systems that combine image-and device-based techniques in order to gather more information about gestures, and thereby enable more accurate recognition. Such hybrid systems are often used to capture hand gestures and facial expressions simultaneously [20].

Recognition methods vary depending on whether the signs are represented by static hand poses or by moving gestures. Recognition of static signing gestures can be accomplished using techniques such as template matching, geometric feature classification, neural networks, or other standard pattern recognition methods to classify the pose [21]. Recognition of dynamic gestures is more complex because it requires consideration of temporal events. It is usually accomplished through the use of techniques such as time-compressing templates, dynamic time warping, Hidden Markov Models (HMMs) [22] and Bayesan Networks [23].

In this paper we are concerned with static or semi-static ASL gestures. The goal is input and recognition of ASL numbers which are represented by static hand-shapes (numbers 0-9) and by hand gestures requiring a very limited range of motion (numbers >9). To capture the hand gestures, we have chosen a direct-device approach because research findings show that this approach yields more accurate results.

3. IMPLEMENTATION

3.1 System (1): hand gesture-based

This interface makes use of a pair of light-weight 18-sensor Immersion cybergloves coupled with an InterSense IS-900 6DOF wrist tracker. Each glove has two bend sensors per finger, four abduction sensors, and sensors for measuring thumb cross-over, palm arch, wrist flexion, and wrist abduction; the wrist tracker uses ultrasonic and inertial tracking to determine the position and orientation of the user's hand within the 3D environment. The user wears the gloves to input ASL number handshapes with the dominant hand, navigation gestures with the non-dominant hand (for instance, the "L" handshape of the manual alphabet to move left, "R, B, F" to move right, backward, and forward respectively), and grasp/release gestures with the dominant hand. For example, the participant can grasp objects by making a closed fist (the 'S' handshape of the manual alphabet). Tracking information enables the program to identify which object in the scene is closest to the user's fingers when the user grabs that object with the gloves. The tracking information also allows that object to remain in the user's grasp as the user moves the hand around the scene. When the user forms the 'neutral' handshape (i.e., the letter 'Y') grasped objects are released at the user's new hand position. Figure 1 shows a student interacting with SMILE using system (1).

In general, our mapping of gestures to specific tasks has been designed so that the association between hand pose and meaning is natural and intuitive for a deaf user. However, one problem was encountered when mapping gestures to grasp and release tasks. Typically, the index-thumb pinch metaphor is used for picking virtual objects and the open fist is used to release control of objects [24]. In our case, we could not use the index-thumb pinch gesture for grasping and the open fist for releasing objects because these hand poses are too similar to number '9' and number '5', respectively. In order to ensure recognition accuracy while maintaining a fairly intuitive gesture-to-meaning mapping, we use a closed hand (the 'S' handshape) for grasping, and a semi-open hand for releasing objects (the 'Y' handshape).

The decision to assign signing and grasp/release tasks to the dominant hand, and navigation tasks to the non-dominant hand is based on research studies in the field of human motor behavior. Literature findings show that the non-dominant hand is generally used for large scale positioning, while the dominant hand is used for fine-grained tasks. Moreover, humans position their dominant hand relative to the coordinate system specified by the non-dominant hand [25].

A problem inherent with implementing gesturing as a means of interaction is 'the fact that natural gesturing involves a series of transitions from gesture to gesture essentially creating a continuum of gesturing' [26]. This makes distinguishing successive gestures very difficult, as the hands and fingers may be constantly moving. In order to ensure recognition accuracy, our interface requires users to form the 'neutral' hand pose between different successive gestures.

Figure 1. User inputs the number '1' ASL handshape with the cybergloves in response to a question asked by the 'lizard' character. SMILE in the background displayed on a 12-screen tiled wall

Recognition. To recognize the hand gestures input via the gloves we have used a neural networks approach based on the Fast Artificial Neural Network Library, (FANN) [27], a freely available package from Sourceforge. This library supports various configurations of neural networks. For SMILE we use the standard complete backward propagation neural network configuration with symmetrical sigmoid activation function. This configuration includes a set of 28 networks, one per hand gesture, with 18 input neurons that corresponds to the 18 angles provided by each data glove. To date, the hand gestures recognized by the system include: 21 ASL number handshapes + 5 navigation gestures + 1 grasp gesture + 1 'neutral' gesture. The 28 gestures are represented in figure 2.

One output neuron for each network determines whether the input configuration is correct (value close to 1) or incorrect (value close to -1 because of symmetrical sigmoid function). The training error was set to 10^{-6} and training of all 28 neural networks for all the input sets was realized in about 10 minutes on a standard laptop with 1.6 GHz Intel Pentium. The neural networks were correctly trained after not more than 10^4 epochs. The detection of one sign was, on the same computer, performed at the rate of about 20Hz . The accuracy rate with registered users was 90%. The accuracy rate with unregistered users was 75%.

Training. The training data set was provided by five ASL signers. Each signer input the 28 hand shapes three times. The training data set for each gesture is composed of 3×5 correct handshapes and 15 incorrect handshapes. For instance, the training set for the letter F (used to move forward) includes the 15 ASL handshapes corresponding to letter 'F', and 15 randomly selected ASL configurations corresponding to different hand gestures (provided by the same signers).

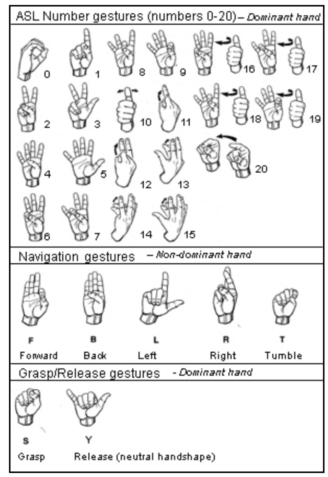

Figure 2. The 28 gestures recognized by system 1

Communication with SMILE. The handshape recognition software runs on a Windows-based laptop. However, the SMILE application, when running in immersive environments, such as a tiled wall or a CAVE-like device, runs on a cluster of several workstations. These workstations may run either Linux or Windows. Thus it is necessary for the recognition software to communicate with the SMILE application through some external mechanism.

The VRJuggler software [28] that SMILE is built on provides a C++ library for external communications via a TCP/IP network, called VPR (VRJuggler Portable Runtime). SMILE uses these external interfaces by first opening a TCP/IP connection to the computer running the handshape recognition application, during the initialization of the SMILE application. When recognition of a handshape occurs, the application sends the recognized gesture over the network via theTCP/IP socket.

The glove device with handshape recognition can be uniquely configured to control many aspects of the SMILE program. Before each frame is drawn, if a gesture has been recognized, the application uses this information to determine what actions should take place. For example, when the handshape 'F' is recognized it instructs the application to navigate the world forward at a fixed speed. The flowchart in figure 3 illustrates communication between the cyberglove, the gesture recognition program, and SMILE.

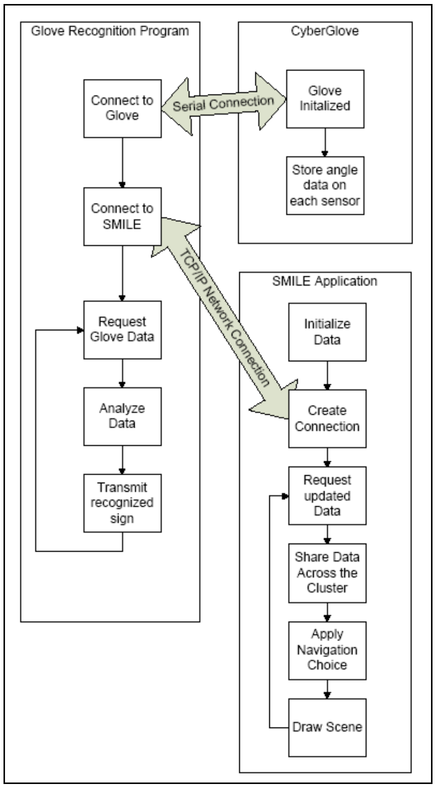

Figure 3. Flowchart illustrating the connection between system (1) and SMILE

3.2 System (2): hand and body gesture-based

This interface makes use of a pair of data gloves (described in section 3.1) and a 19-marker MetaMotion optical motion capture system with a setup of 4 or 6 cameras. Users can input ASL signs and can grasp and release objects simultaneously with the dominant and non-dominant hand, respectively. They can stand anywhere within the capture area and move through the environment by stepping forward, back, left, or right, and can rotate the 3D scene by stepping forward and pointing their toe in the direction of rotation.

In order to accomplish motion through the 3D environment the positions of two markers are compared. The waist, the most centralized position, is stored as the origin of the space. The right ankle position is compared to the waist to determine what direction the user is stepping. The distance the foot is away from the user and the direction relative to the user's waist orientation determine the speed and direction of navigation in SMILE, respectively. Two other markers are then compared, the right ankle position and the right toe position. The difference between the positions of these points can be used to create a vector that is then normalized and used with the dot product to determine the angle the foot is pointing (relative to the user's leg in order to rotate the world). This way, by simply stepping forward and pointing the toe, the user can rotate the 3D scene. To avoid accidental motion, a 'dead zone' has been established for small angles and distances. When the foot is placed close to the waist, or with a small angle of rotation, no motion occurs. The user must place her foot outside the dead zone in order to translate or rotate. The dead zone limits were set through trial and error until they reached a point where triggering of motion required deliberate action by users, without becoming uncomfortable. Figure 4 shows a student using the motion tracking system to travel through SMILE.

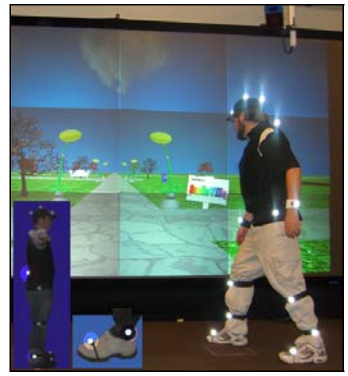

Figure 4. A user wears the optical mocap suit and steps forward to navigate through SMILE. The waist, ankle and toe markers are highlighted on the left.

Communication with SMILE. The motion capture system operates on a set of Windows workstations dedicated to processing video images and determining marker positions. This system is also separate from the rendering cluster that the SMILE application runs on. Therefore, the motion capture system must also communicate with the SMILE application via an external connection. This is accomplished in the same way that the connection between interface (1) and SMILE is designed (see figure 5). When the motion capture system has successfully recognized the position of the 19 markers on the participant, the data are stored and sent over the network via the TCP/IP socket.

4. DISCUSSION

Both interfaces have their own strengths and weaknesses. The main advantage of interface (1) is its portability and, therefore, its applicability to a variety of immersive VR devices, including low-cost fish tank systems. The main disadvantage is the fact that it does not fully support concurrent tasking. The user can navigate through the environment while carrying an object or while inputting a sign, but the three tasks of travel, sign input, and object manipulation cannot occur at the same time. Another limitation of the current implementation is the inability to control speed of travel. Future work involves experimenting with various hand gesture metaphors to control the rate of motion in a natural way.

In addition to support of simultaneous tasking, one of the strengths of interface (2) is the user ability to navigate the virtual world using the lower body. Traveling through the 3D environment by stepping in different directions requires little or no cognitive mapping to perform, therefore it is one of the most usable means of virtual locomotion in immersive environments. Another advantage of system (2) is support of input and recognition of ASL signs that require arms, spine, and shoulder motions. Although ASL signs for mathematics do not rely heavily on arms and shoulder movements, many other ASL signs involve motion of the entire upper body. System (2) is not restricted to input of math signs only, it could be easily extended to input and recognition of all ASL signs. The main disadvantage of system (2) is the fact that it is not easily portable and, therefore, restricted to use in stationary VR devices.

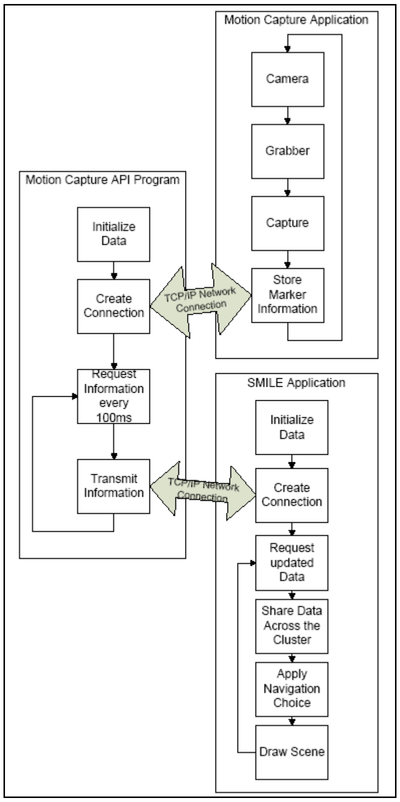

Figure 5. Flowchart illustrating the connection between system (2) and SMILE

One main limitation of both systems is the high cost of the hardware components. Currently, the cost of the gloves is a major obstacle to immediate dissemination of interface (1) to educational institutions for the Deaf. We are investigating more cost-effective, types of gloves available on the market (http://www.vrealities.com/glove.html), as well as gloves created by researchers specifically for input of signing gestures [29].

System 2 was designed primarily to experiment with full-body interaction in stationary, multiple screen immersive devices, therefore we are not concerned with the high cost of the equipment at this stage of development. Presently, this interface could be used in centers of informal education, such as museums, or in research centers. However, we anticipate that motion capture technology will become more affordable in the next few years and might provide one of the most effective and natural interaction systems for immersive applications for hearing and non-hearing users.

Another limitation of both interfaces is that recognition is presently restricted to ASL numbers 0-20. In future implementations recognition will be extended to include numbers 1-1000, decimals, fractions, and mathematical operators. In addition, one characteristic of ASL numbers is that they are signed in different ways depending on their meaning (i.e., numbers used to describe quantities– cardinals–, numbers for monetary values, numbers associated with tell-time activities, etc.). For instance, for dollar numbers 1-9, the number hand-shape is associated with a twisting motion (wrist roll) to indicate dollars; for cent numbers, one possibility is to sign the cardinal number and fingerspell the word c-e-n-t-s. In order to be truly effective and usable, sign language e recognition systems need to consider these variations.

5. CONCLUSION

The interfaces presented in this paper are still to be considered prototypes since many of their features are only at a first stage of development and present numerous limitations. But in spite of their weaknesses, they are, to our knowledge, the first immersive sign language interfaces that support input and recognition of ASL math signs, as well as natural and intuitive navigation and interaction.

Many aspects of the interfaces still need to be tested and improved. A comparative evaluation of the interfaces will be carried out in Fall 2007 in collaboration with the Indiana School for the Deaf (ISD). In addition to assessing the usability of the interfaces, the full-scale evaluation will address the problem of signer-independent recognition. An ideal sign recognition system should give good recognition accuracy for signers not represented in the training data set (unregistered signers) [31]. Inter-person variations that could impact sign recognition include different signing styles, different sign usage due to geographical and social background, and fit of gloves. Many works report that recognition accuracy for unregistered signers decreases severely (by 30-40%) when the number of signers in the training set is small, and when the signs involve significant, continuous movement. In the case of our interfaces we are concerned with the problem of degradation of recognition accuracy due to fit of the gloves (since SMILE is aimed at children of different ages -5 - 11 years-), but we anticipate good recognition results considered that many of the math signs are static or involve minimal motion. Studies show that recognition accuracy for unregistered signers is relatively good when only hand shapes and/or limited motion are considered [30]. So far, 7 unregistered signers have used our interfaces; recognition accuracy was 75%.

In conclusion, research findings show that automatic analysis of Sign Language gestures has come a long way, and current work can successfully deal with dynamic signs which involve movement and which appear in continuous sequences. However, much remains to be done before sign language interfaces may become commonplace in face to face computer human interaction in general, and in immersive applications in particular. One aspect that needs further investigation is recognition of grammatical inflections and mimetic signs, and non-manual signals (NMS). While interpretation of NMS in conjunction with gesture recognition is fundamental for understanding sign language communication in general [31], it is not so important for ASL mathematics. Therefore, considered that most ASL mathematics signs are represented by static or semi-static signs and do not rely greatly on NMS, we believe that the realization of a natural immersive American Sign Language interface for mathematics is a goal achievable in the near future.

6. AKNOWLEDGEMENTS

This research is supported by NSF-RDE grant #0622900 and by the Envision Center for Data Perceptualization at Purdue University.

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