Automated Recognition of Hand Gestures for Crane Rigging using Data Gloves in Virtual Reality

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Abstract –

Construction safety training through Virtual Reality (VR) environments offers workers an interactive and immersive experience. Many complex interactions and realistic scenarios are possible in VR using accessories such as data gloves and trackers which allow data recording on incidents. For example, misinterpretation of hand signals construction workers give during operations may result in severe accidents on construction sites. This study proposes automatic gesture recognition to identify hand signals for crane rigging operations in VR training. The developed gesture recognition algorithm tracks information from a data glove and a tracker. Preliminary data on movements and orientation of hands and fingers were recorded. Mathematical models of hand gestures were created based on finger movement data. Gesture rules were created based on the rotation and orientation of the hand. The gesture models were combined with the gesture rules to develop the algorithm for automated gesture recognition. Final experiments estimated the efficacy of the proposed method in automatically recognizing crane rigging signals in real-time. The performance is evaluated by comparing the identified hand gestures with independently created ground truth labels. The proposed method identified static hand gestures with an average accuracy of 96.55 percent. This method recognizes the gestures along with the hand movements and displays the results in real-time equivalent to dynamic gesture recognition. More refined dynamic gesture recognition based on this method is in progress.

Keywords –

Gesture recognition; Virtual reality; Construction safety; Safety training; Data gloves; Hand motion tracking

1 Introduction

Virtual Reality (VR) environments provide new possibilities for advancing construction safety training. These computer-aided training methods develop an interest in workers and ensure their active participation [1], [2]. The workers can be subjected to complex and dangerous scenarios in the virtual environment without the possibility of injuries [3]. The trainees can receive personalized feedback based on their performance assessed from the data collected during training [4]. Multiplayer serious games create collaborative learning spaces for the participants [5] and dynamically updated VR training exposes the trainees to the latest work environment according to the construction progress [6].

Hand gestures are widely used for communication on construction sites. They enable effective communication irrespective of the construction noises and language barrier between the workers [7]. There are standard hand signals for operations such as crane rigging [8]. However, misinterpretation of these predefined hand signals by the operator of the cranes or any other machines may cause severe accidents [9]. According to the U.S Bureau of Labor Statistics, an average of 42 crane-related deaths occur per year and 43 percent of the fatal crane injuries are from the construction industry [10]. Human error account for 90 per cent of crane accidents and proper training of crane operators and signalers is essential [11]. Automatic recognition and interpretation of the hand gestures may potentially assist in effective communication between the signaler and the operator. It improves communication in VR training scenarios involving multiple workers similar to the actual construction site. Automated gesture recognition in VR coupled with the collection of trainees' behavioral data [6] can quantitatively estimate the effectiveness of VR based training methods. The objective of the current study is to automatically recognize hand signals for crane rigging in virtual reality (VR) through data gloves. The scope of this study is limited to identifying six classes of hand gestures: five hand signals, including stop, raise boom, lower boom, hoist load and lower load, and any other unidentified hand gestures.

This paper is organized as follows. Section 2 provides the background on gesture recognition in VR and related terminologies. The study's methodology is described in Section 3 and an overview of the experiment and data collection is provided in Section 4. The development of the gesture recognition algorithm is in Section 5. Section 6 presents the gesture recognition method and Section 7 describes its validation. The results and discussion are given in Section 8. Finally, Section 9 concludes the paper with findings and an outlook for future work.

2 Background

2.1 Hand Anatomy and Movements

The human hand is a complex biomechanical device that evolved over millions of years to achieve the current level of motor skills. It is capable of performing numerous tasks that involve a variety of movements. A typical human hand consists of a wrist, a palm and five fingers. The hand is composed of 27 bones as illustrated in Figure 1. The bones are categorized as 1) carpals in the wrist [short bones, 8 no.], 2) metacarpals in the palm [long bones, 5 no.], and 3) phalanges in fingers [long finger bones, 14 no.]. Each of the four fingers except the thumb is composed of proximal phalange, intermediate phalange, and distal phalange. The thumb has only two phalanges, proximal phalange and distal phalange. The placement of the metacarpal bone of the thumb enables its distal phalanges to oppose the distal phalanges of other fingers. This configuration of the thumb allows humans to grab objects in hand.

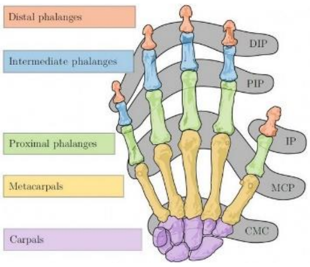

Figure 1. Finger joints of a human hand [12].

The joints in the hand facilitate various movements of fingers, as illustrated in Figure 2. Hinge joints prove 1 DOF (Degree of Freedom), i.e. flexion or extension. Saddle joints provide 2 DOF, i.e., flexion or extension and abduction or adduction. The metacarpophalangeal (MCP) is a saddle joint, whereas proximal interphalangeal (PIP), distal interphalangeal (DIP) and interphalangeal (IP) are hinge joints. In addition to carpometacarpal (CMC) joints, the thumb has two joints (MCP and IP) and all other fingers have three joints (MCP, PIP, and DIP).

2.2 Gesture Interactions and Recognition in Virtual Reality

Gesture interactions in VR are facilitated through different input devices such as wearable sensor-based devices, touch-based devices, and computer vision-based devices [13]. The wearable devices include data gloves, inertial sensors and myoelectricity sensors [14], [15]. The touch-based devices comprise touch screens and stylus pens. Different types of cameras such as monocular, binocular, and depth cameras constitute computer vision-based devices. The data gloves can act as an input device to collect finger postures and movements. Besides, some data gloves have additional features to provide haptic feedback to the users, creating a more realistic experience [16]. Some of the advantages of data gloves include high recognition accuracy, no environmental influence, small data sets, and low computational power requirement. However, it has some shortcomings such as high cost, low flexibility and the need for frequent calibration.

Gesture recognition methods in VR can be categorized as methods based on 1) wearable devices, 2) touch technology, 3) computer vision, and 4) multimodal interaction technology. Data gloves are one of the most commonly used wearable devices in VR. The gesture recognition based on wearable devices involve collecting finger posture data, extracting spatiotemporal parameters, selecting effective parameters, and model training [17] or identification by an intelligent algorithm [18]. The gesture recognition based on touch technology can be further divided into single touch and multitouch recognition. The $1 algorithm is a simple algorithm for identifying single-stroke gestures [19]. It has been modified to identify multi-stroke gestures with reduced complexity using point clouds [20]. Currently, computer vision-based gesture recognition methods are being widely implemented. This method consists of data collection through cameras, preprocessing, gesture segmentation, gesture analysis and gesture recognition [21]. Multimodal interaction technologies use two or more modalities of communication to recognize the instructions from the user [22]. These methods attempt to incorporate a more natural way of communication by the user for virtual interaction.

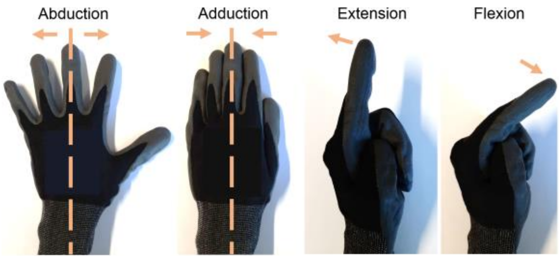

Figure 2. Motions of human fingers of a construction worker wearing protective gloves.

2.3 Significance of the Current Study

Data-driven methods such as deep learning have been widely used for gesture recognition. However, the existing methods have several drawbacks. These methods often require large datasets for training that may not be available for newly created VR training scenarios. The performance of computer vision-based methods depends on environmental factors such as light, skin color, and occlusion. The methods require several image processing techniques which might affect the recognition accuracy. The computer vision-based method may not capture the signals correctly in crane rigging operations unless multiple cameras are installed at different levels. Autonomous cranes might depend on the ground-based human operator who wears intelligent gloves.

The interactions with VR controllers often lack the realistic experience during construction safety training. Besides, the nuances of finger movements and seamless coordination between real and virtual avatars are essential in collaborative training environments[23]. Therefore, data gloves and trackers were introduced to enhance the interactive and realistic experience in VR training. Automatic gesture recognition during the training potentially improves the communication between the trainees. Thus, a gesture recognition method for VR training has been developed in this study. A training scenario involving a signaler and a crane operator is envisioned where the communication has been enhanced by automatic gesture recognition. A gesture recognition algorithm has been developed based on the information streams from data gloves and trackers. The proposed method identifies and displays the gestures in real-time during the VR training.

3 Methodology

The overall methodology for this study consists of experiments and data analytics. First preliminary experiments were conducted to collect various data such as finger movement and hand orientation required for gesture recognition. Then, mathematical models of the hand gestures were created based on finger movement data. These gesture models were combined with the orientation data to develop the algorithm for automated gesture recognition. After that, experiments were designed to capture the efficacy of the proposed method in automatically recognizing crane rigging signals. Next, experiments were conducted to collect the data in run-time and implement the proposed method. The performance of the method is evaluated by comparing the predicted hand gestures with independently created ground truth labels. The subsequent sections will describe more details regarding each of these steps.

4 VR Experiments and Data Collection

The current study conducts virtual reality experiments in two stages. The serious games for the experiments were developed in the game engine software Unity. The preliminary experiments in the first stage are for developing the gesture recognition algorithm (described in Section 6). The VR experiments in the second stage are for validating the gesture recognition method (described in Section 8). The user wears a data glove and tracker while making the specified gestures in both cases. The data corresponding to hand and finger movements were collected in real-time during the experiments. Figure 3 shows the user wearing the data glove and tracker ready for the experiment. The Prime X Haptic VR data glove [24] is used for finger tracking. This data glove contains a flex sensor skeleton to capture the bending of the fingers. It also contains an Inertial Measurement Unit (IMU) with nine DOF (Degree of Freedom) per finger to capture relative movements. Collection and visualization of the data from the data glove are enabled by the data handling software Manus Core. This software also helps to live stream the finger movement data to Unity. The VIVE Tracker (3.0) [25] is mounted on the data glove to track hand movements. The tracker enables seamless coordination between the real hand and its virtual counterpart in the VR environment. The tracking data is collected and streamed to Unity through the SteamVR application [26].

Figure 3. A user wearing the data glove and tracker ready for gesture recognition.

5 Development of Gesture Recognition Algorithm

An overview of developing the gesture recognition algorithm is illustrated in Figure 4. It starts with preliminary experiments containing five selected hand signals for crane rigging. The experiments were conducted to understand the nature of hand gesture data for developing the recognition algorithm. The user makes the selected gestures in the experiment wearing a data glove and a tracker. Each set of the experiment contains one hand gesture. The current study has selected five crane rigging signals as shown in Figure 5: 1) stop, 2) raise boom, 3) lower boom, 4) hoist load, and 5) lower load. These hand signals are dynamic i.e., they involve movements of the hand along with the hand gestures. The proposed method is designed to recognize hand gestures in a static position (static hand signals). However, continuous real-time identification of gestures enables dynamic gesture recognition.

The finger data is live-streamed to the Manus Core and visualized in the Manus dashboard. The data viewer displays values of flexion, extension, abduction, adduction, thumb rotation and wrist rotation. The flexion and extension are estimated with respect to the finger joints, whereas abduction and adduction are estimated with respect to the midline of the hand and a finger joint. The finger data is simultaneously streamed from the Manus Core to Unity. Currently, the gesture models were created in Unity as described in the next paragraph.

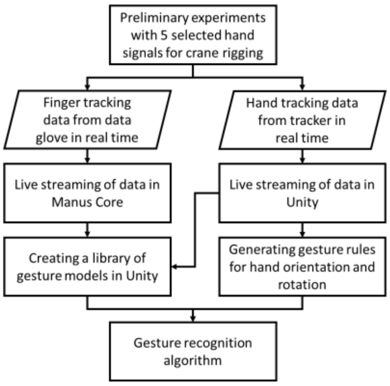

Figure 4. Development of gesture recognition algorithm

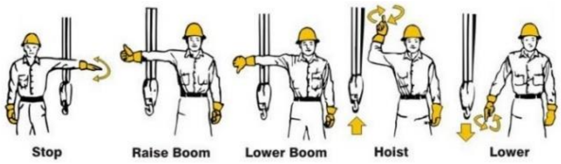

Figure 5. Selected crane rigging signals for this study [8]

Three hand gestures were selected to represent the finger positions in the five crane rigging signals. The selected hand gestures are: 1) 'thumbs up' (only thumb is straight, all other fingers are flexed), 2) 'pointing' (only index finger is straight, all other fingers are flexed) and 'high five' (all fingers are straight). Note that only finger movements can be tracked with the data glove. Additional information about the hand movement is required for identifying the crane rigging signals. Mathematical models were created for the three selected gestures in Unity. The mathematical model of a gesture defines the movement of each finger in a relative scale with respect to the finger joints and/or midline of the hand. Flexion and extension of a thumb are specified based on CMC, MCP and IP; and that of other fingers based on MCP, PIP and DIP. Abduction and adduction of a thumb are specified based on CMC, whereas that for other fingers based on MCP. Thus, a library of predefined gesture models was created in Unity. Currently, the library contains three gesture models, each of which represents the finger positions of the selected hand signals as shown in Table 1.

After creating the gesture library, gesture rules were generated from the hand tracking data. The movements of the hand are tracked in real-time through the VIVE tracker. The real hand will appear as a game object in Unity and the same object will be seen by the users in the virtual environment. The game object of the hand is hereafter referred to as the hand object. The hand object has an attribute called 'transform' that contains the position, rotation and scale of the object in the virtual environment. The current study uses the transform of the hand object to create rules for recognizing hand gestures.

Table 1. Hand signals and corresponding gesture models in the library

Label	Hand signal	Gesture model	Need more information for recognition?
0	No recognition	-	Yes
1	Stop	HighFive	Yes
2	Raise boom	ThumbsUp	Yes
3	Lower boom	ThumbsUp	Yes
4	Hoist load	Pointing	Yes
5	Lower load	Pointing	Yes

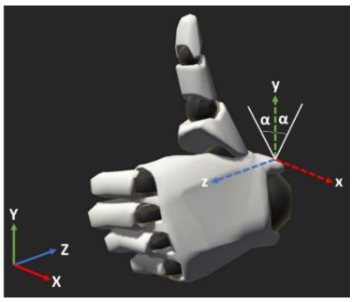

Figure 6. Schematic of the Gesture rule for raise boom hand signal

Consider the example of the hand signals for 'raise boom' and 'lower boom'. Both of these hand signals have the same gesture model (ThumbsUp) to represent their finger positions. Therefore, rotation or orientation of the hand in the virtual environment is essential to distinguish between these hand signals. Thus, the gesture rules for recognizing these hand signals involve a specific range of values for these parameters from the viewer's perspective. Figure 6 shows a schematic representation of one of the gesture rules for the raise boom hand signal.

Here, the solid arrow marks represent the global coordinate system (X, Y, Z) for the virtual environment and dotted arrow marks represent the location coordinate system (x, y, z) for the hand object. The tolerance of rotation of the hand object about the y axis is denoted by α. The gesture rule in this scenario is: if $\alpha <= 30^0$ for the gesture model 'ThumbsUp', the hand gesture is 'raise boom'. Note that this is a simplified illustration of a gesture rule. Orientation and rotation of the hand object with respect to all other axes will be specified in the actual gesture rule. The gesture recognition algorithm is developed by combining the gesture rules and gesture models. A detailed description of the gesture recognition method is given in the next section.

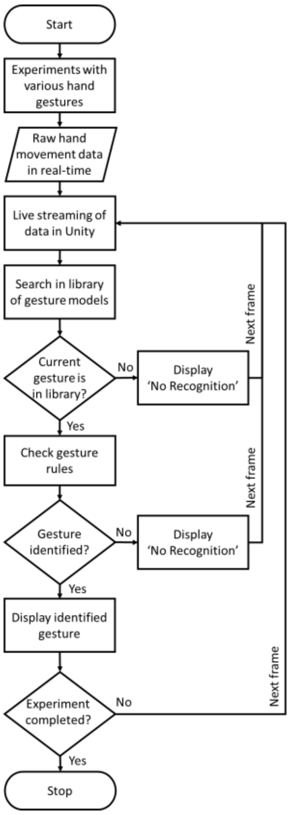

Figure 7. Gesture recognition method.

6 Gesture Recognition Method

The automated gesture recognition method proposed in this study is shown in Figure 7. First, the algorithm is implemented in actual virtual reality experiments containing various hand gestures. The raw hand movement data collected by the tracker and the finger movement data from the data glove are live-streamed into Unity. The gesture recognition algorithm is attached as a script to the hand object in Unity. The recognition algorithm runs in a fixed interval for accurately capturing the physics movements of the hand object. The gesture data from the user is evaluated in each run. First, the gesture library is searched to see if the current finger movement data match any of the predefined gesture models. If none of the gesture models matches the current gesture data, display 'No recognition' and proceed to the next frame. If any of the gesture models match with the current finger movement data, check the associated gesture rules. The orientation and rotation of the hand object are estimated, and the gesture rules are evaluated. If none of the rules is satisfied, display 'No recognition' and proceed to the next frame. Otherwise, determine the hand signal based on the gesture rules satisfied. Then display the identified hand signal and check whether the experiment is completed. If the experiment is complete stop the iteration. Otherwise, proceed to the next frame.

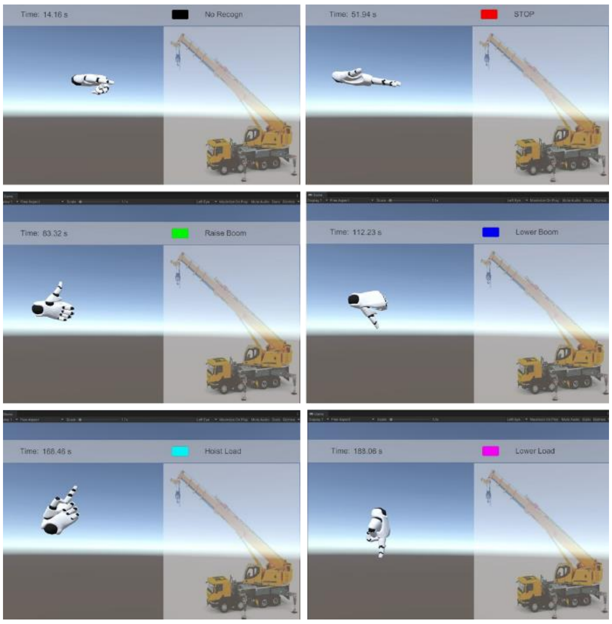

Figure 8. Conveying hand signals to the crane operator in virtual reality. The real-time predictions by the recognition method for each hand signal are displayed with the time stamp.

7 Validating Gesture Recognition Method

The proposed gesture recognition method (Figure 7) is validated by virtual reality experiments where the user acts as a signaler for a crane operator. In the experiments, the user wearing the data glove and the tracker make various hand gestures for a specific interval. The gestures involve hand signals for crane rigging operations and some random gestures. The gesture data are collected from the data glove and trackers in real-time during the experiments. Simultaneously the collected data is analyzed using the proposed method and results were also displayed in real-time. The display contains the predicted hand gesture, an associated color and time stamps as shown in Figure 8. The predictions are also logged in a text file (.txt) as entries in the format “time (in seconds), predicted gesture, label”; e.g., “72.82 RaiseBoom 2”. The entire experiment is recorded in the game view using the Unity recorder. The recorded videos of the experiments with time stamps were used to create ground truth labels for the gestures. The experiment was repeated five times. The accuracy of the recognition method is estimated as an average of all the repetitions.

8 Results and Discussion

The results of gesture identification and related discussion are presented in this section. The accuracy of the proposed recognition method for the dataset generated from each repetition of the experiment is presented in Table 2. The gesture recognition method has an average accuracy of 96.55 percent. The method delivers an accuracy above 95 % for all datasets except the first one. The proposed method is designed to recognize static hand gestures. However, the experiments for validation used dynamic gestures to understand the potential of the method in identifying actual crane rigging signals. Nevertheless, the gesture recognition method delivered an overall good performance.

Table 2. Performance of the recognition method.

Dataset	Accuracy
1	93.86%
2	96.86%
3	98.58%
4	95.60%
5	97.87%
Average accuracy	96.55%

The recognition results for dataset 4 is illustrated in Figure 9 and the results with highlighted misclassifications are presented in Figure 10. The gesture recognized by the proposed method is plotted in grey and the ground truth values are plotted in blue. The lines overlap whenever the recognized gesture is correct. Thus, the misclassifications can be seen are the misaligned parts of the grey line that was highlighted in black in Figure 10. The hand signal for ‘stop’ (Label 1) and other undefined or random gestures (Label 0) are identified without any mistakes. However, some instances of the hand signals for ‘raise boom’ (Label 2), ‘lower boom’ (Label 3), ‘hoist load’ (Label 4) are misidentified as the undefined class. The number of misidentifications is fewer compared to the frequency of the function call (50 times per second) for gesture recognition. Therefore, these misidentifications may not result in serious communication problems while displaying the results continuously. Similarly, some instances of the hand signal ‘lower load’ (Label 5) are wrongly identified as ‘hoist load’ (Label 4). These misidentifications need to be addressed carefully since they belong to the opposite category of hand signals. The potential reasons for the misidentifications are the strict bounds for hand orientation and rotation. More flexible and robust gesture rules are being explored with information from additional trackers.

The overall accuracy of the recognition method per hand gesture is given in Table 3 and illustrated in Figure 11. All gestures have been recognized with accuracy above 90 percent, and some of them have close to 100 percent accuracy. Therefore, the proposed method shows the potential for improving the VR safety training scenarios involving construction site communication. The undefined or random gestures and hand signals for ‘stop’, ‘lower boom’ and ‘hoist load’ are identified with high accuracy. However, identifying the hand signals for ‘raise boom’ and ‘lower load’ needs further improvement. Since opposite hand signals of these classes were identified with high accuracy, the gesture models seem robust to represent the finger movement. More attention is required to refine the gesture rules that define hand orientation and rotation during signaling.

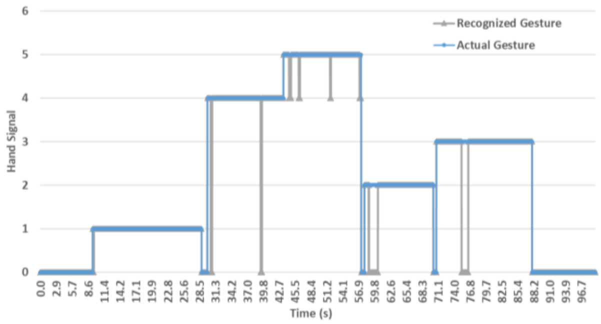

Figure 9. Gesture recognition results for dataset 4. Gesture labels are 0: No recognition, 1: Stop, 2: Raise boom, 3: Lower boom, 4: Hoist load, and 5: Lower load.

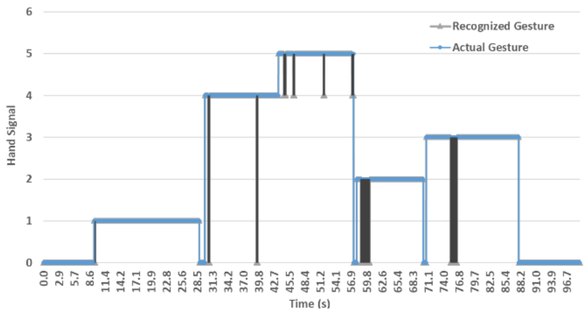

Figure 10. Gesture recognition results for dataset 4 with misidentifications highlighted in black. Gesture labels are 0: No recognition, 1: Stop, 2:

Raise boom, 3: Lower boom, 4: Hoist load, and 5: Lower load.

Table 3. Performance of recognition per hand gesture.

Label	Hand gesture	Overall prediction accuracy
0	No recognition	99.78%
1	Stop	99.29%
2	Raise boom	90.61%
3	Lower boom	98.60%
4	Hoist load	97.64%
5	Lower load	91.13%

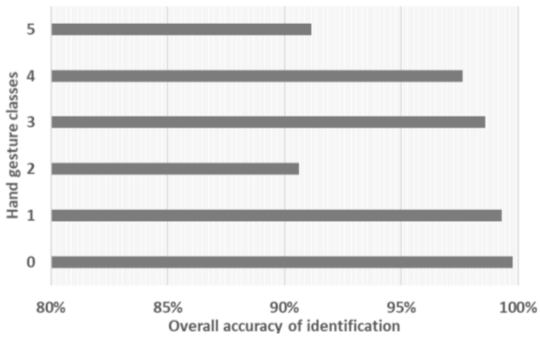

Figure 11. Accuracy of identification per hand gesture classes.

9 Conclusions and future work

An automatic gesture recognition method for identifying hand signals for crane rigging in virtual reality is proposed in this study. The gesture recognition method is developed based on tracking information from a data glove and a tracker. Gesture models were created to represent the finger movement during hand signals. The rotation and orientation of the hand for a signal are defined by gesture rules. A gesture recognition algorithm is developed by combing the gesture models and rules. The proposed method is validated by virtual reality experiments containing various hand gestures.

The gesture recognition method delivered an average accuracy of 96.55 percent. Most of the gesture classes were identified with high accuracy. The misidentifications were mainly attributed to the bounds of the gesture rules. More robust gesture rules are being developed based on independent information from other tracking devices. The good recognition performance shows that this method can improve VR safety training scenarios involving communication between workers. Incorporating data gloves in VR helps articulate the hand signals better than conventional controllers.

This study can be further extended to quantitatively estimate the effectiveness of the current communication methods that are being utilized in the construction site operations. Although the proposed method is designed to recognize static hand gestures, it can continuously recognize the hand gestures and display the results in real-time. Therefore, it is equivalent to dynamic gesture recognition to a certain extent. The future study involves incorporating additional trackers to capture more complex and dynamic hand gestures. Besides, haptic feedback from the data glove is being implemented to enhance the learning experience of the workers.

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