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Eye-Track Modeling of Problem-Solving in Virtual Manufacturing Environments

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Abstract

Problem-solving focuses on defining and analyzing problems, then finding viable solutions through an iterative process that requires brainstorming and understanding of what is known and what is unknown in the problem space. With rapid changes of economic landscape in the United States, new types of jobs emerge when new industries are created. Employers report that problem-solving is the most important skill they are looking for in job applicants. However, there are major concerns about the lack of problem-solving skills in engineering students. This lack of problem-solving skills calls for an approach to measure and enhance these skills. In this research, we propose to understand and improve problem-solving skills in engineering education by integrating eye-tracking sensing with virtual reality (VR) manufacturing. First, we simulate a manufacturing system in a VR game environment that we call a VR learning factory. The VR learning factory is built in the Unity game engine with the HTC Vive VR system for navigation and motion tracking. The headset is custom-fitted with Tobii eye-tracking technology, allowing the system to identify the coordinates and objects that a user is looking at, at any given time during the simulation. In the environment, engineering students can see through the headset a virtual manufacturing environment composed of a series of workstations and are able to interact with workpieces in the virtual environment. For example, a student can pick up virtual plastic bricks and assemble them together using the wireless controller in hand. Second, engineering students are asked to design and assemble car toys that satisfy predefined customer requirements while minimizing the total cost of production. Third, data-driven models are developed to analyze eye-movement patterns of engineering students. For instance, problem-solving skills are measured by the extent to which the eye-movement patterns of engineering students are similar to the pattern of a subject matter expert (SME), an ideal person who sets the expert criterion for the car toy assembly process. Benchmark experiments are conducted with a comprehensive measure of performance metrics such as cycle time, the number of station switches, weight, price, and quality of car toys. Experimental results show that eye-tracking modeling is efficient and effective to measure problem-solving skills of engineering students. The proposed VR learning factory was integrated into undergraduate manufacturing courses to enhance student learning and problem-solving skills.

1. Introduction

Manufacturing serves as a key wealth-creation engine and a vital provider of jobs in the United States. Rapid technological advances call upon manufacturing industries to evolve and respond to fierce-competing markets, new production paradigms, and data proliferation [1]. As the future workforce in manufacturing industries, engineering students need efficient and effective learning schemes to keep up with the technological advancements. A learning factory was developed by the Pennsylvania State University in 1994 to provide a close-to-industry environment to engineering students [2]. This learning factory involves a college-wide infrastructure to support industry-related design projects. Students can be involved in hands-on activities and solve real-world problems in a realistic manufacturing environment. However, some universities may not be able to introduce the latest manufacturing systems and technologies into the learning factory due to limited financial resources. Also, manufacturing safety is important to reduce the risks of workplace injury. Injuries to students may cause significant compensation and medical treatment costs [3]. Therefore, it is imperative to develop a cost-effective and safe learning environment for engineering students to get hands-on training.

Virtual reality (VR) has emerged as a new technology which simulates the real-world experience in an immersive virtual environment. This combined with the advances in computational power and the maturation of game engine technologies allow students to interact with virtual objects in ways never possible before. Therefore, VR can serve as an enabling tool to mimic the physical learning factory. A VR learning factory is flexible to changes in manufacturing systems, thereby providing students with the state-of-the-art manufacturing technologies. On the other hand, the availability of eye-tracking sensing technology facilitates the acquisition and analysis of eye movements in the VR learning factory. Eye movements allow for revealing cognitive processes of engineering students while solving problems [4]. Thus, it is significant to integrate the VR learning factory with the data analytics of eye movements, so as to understand and enhance problem-solving skills of engineering students.

In this research, we integrate gaming technology, VR and eye-tracking sensing to evaluate and enhance problem-solving skills of engineering students. First, we simulate a learning factory in a VR game environment. The VR learning factory is built in the Unity game engine with the HTC Vive VR system for navigation and motion tracking. A headset custom-fitted with Tobii eye-tracking technology identifies the coordinates and objects a user is looking at. In the VR environment, engineering students see through the headset a virtual learning factory composed of a series of workstations and can interact with the workpieces in the virtual environment. Second, engineering students are asked to design and assemble car toys that satisfy predefined customer requirements while minimizing the total cost of production in the VR learning factory. Third, eye movements of engineering students are analyzed with data-driven models to evaluate the problem-solving skills of engineering students.

2. Relevant Literature

2.1 Learning Factory

Understanding manufacturing processes, dealing with change, and working collaboratively have been reported as the most important technical challenges that new engineering graduates face in manufacturing industries [5]. It is crucial to bridge the gap between engineering graduates' problem-solving skills and competencies needed in manufacturing industries. The learning factory was first developed for students to gain hands-on experience by applying classroom knowledge to solve real-world engineering problems offered by manufacturing industries [2]. In the past decade, the learning factory was tailored and evolved to enhance hands-on training and learning experience for students and practitioners [6]. For example, the learning factory for lean production at the Technical University of Munich is designed for implementing theoretical principles into a real lean production environment [7]. In the new era of Industry 4.0, a significant number of learning factories strive to incorporate digital twin concepts through creating their virtual representations. However, convergence between physical and virtual learning factories remains to be an unresolved challenge [8]. The availability of VR enables the development of virtual learning factories by providing an immersive virtual environment in a 3D simulation. VR is flexible to changes in modern manufacturing systems and encourages collaboration through a shared visualization [9]. Combined with player modeling techniques, learning factories can bring about effective learning experiences for students [10]. It is promising to utilize VR technology to enhance the learning experience in learning factories.

2.2 Eye-Tracking in Complex Problem-Solving

Complex problem-solving requires many cognitive activities. The availability of eye-tracking technology facilitates the study of cognitive activities through measuring an individual's eye movements [11], [12]. Eye-tracking has been utilized to evaluate the behaviors of individuals when they solve science problems [13]. In this study, a group of students is displayed multi-choice problems in biology, chemistry, and physics. Eye-tracking data including the location of eye fixation on the computer screen, scan path, durations of fixation and between fixations are recorded when students solve problems. It was found that students with higher levels of a specific domain knowledge show quantifiably different eye-movement patterns from students who have lower-level knowledge in that specific domain. Moreover, eye-tracking data have been shown effective to distinguish students with different levels of expertise. Eye-tracking data such as fixation duration and the number of fixations are also used to study the role of diagrams in problem-solving [14]. Eye-tracking data analysis suggests that students split attentions between the diagram and text and tend to spend less time on the text. It is shown that the cognitive load is reduced when both formats are presented in problems and more cognitive resources are saved for further steps in problem-solving. All these research studies suggest that eye-tracking is effective in studying the problem-solving processes by revealing individuals' cognitive activities. However, little has been done to quantify the problem-solving performance of individuals. Therefore, it is imperative to utilize data-driven analytics of eye-tracking data to evaluate and enhance problem-solving skills, especially in the engineering field.

2.3 Quantification and Modeling of Problem-Solving

Quantification and modeling of problem-solving skills can help in understanding how problem solvers analyze and solve the problems. This allows for developing effective strategies for teaching and enhancing problem-solving skills. A few studies discussed the development of models to quantify and understand problem-solving. For example, a study was conducted to model visual problem-solving as analogical reasoning [15]. The study developed a model based on comparing images via structure mapping which involves aligning the common relational structure in two images to identify commonalities and differences. It was found that the proposed model matches adult human performance and that problems which are difficult for the model are also difficult for people. In another study, a modeling approach was proposed to help students learn expert problem-solving [16]. The proposed approach allows modeling physics to be integrated into a typical introductory college mechanics course. A third study developed models of problem-solving to study children's problem-solving process [17]. According to the study, the conception of modeling the problem-solving process could provide a unifying framework for thinking about problem-solving in children.

In this research, we integrate eye-tracking and VR to collect data from participants during the problem-solving process. The collected data is used to develop models that allow for quantifying and understanding the behavior of problem solvers and how their performance is compared to experts. Performance measures are then developed to reflect the problem-solving skills.

3. Research Methodology

The proposed research methodology develops a VR learning factory to enhance student understanding of manufacturing concepts. Data-driven models are integrated with eye-tracking sensing to evaluate and enhance problem-solving skills of engineering students in the VR learning factory. As shown in Figure 1, a physical learning factory is first developed to simulate a manufacturing system where students can assemble physical car toys [18]. Second, a VR learning factory is developed to mimic the physical factory. Eye-tracking sensing is integrated with VR to record students' eye movements during the problem-solving process. Third, problem-solving skills of students are measured through eye-tracking data analytics. The analytical models are evaluated by comparison with a VR-based composite index which reveals the students' assembly performance in the VR learning factory.

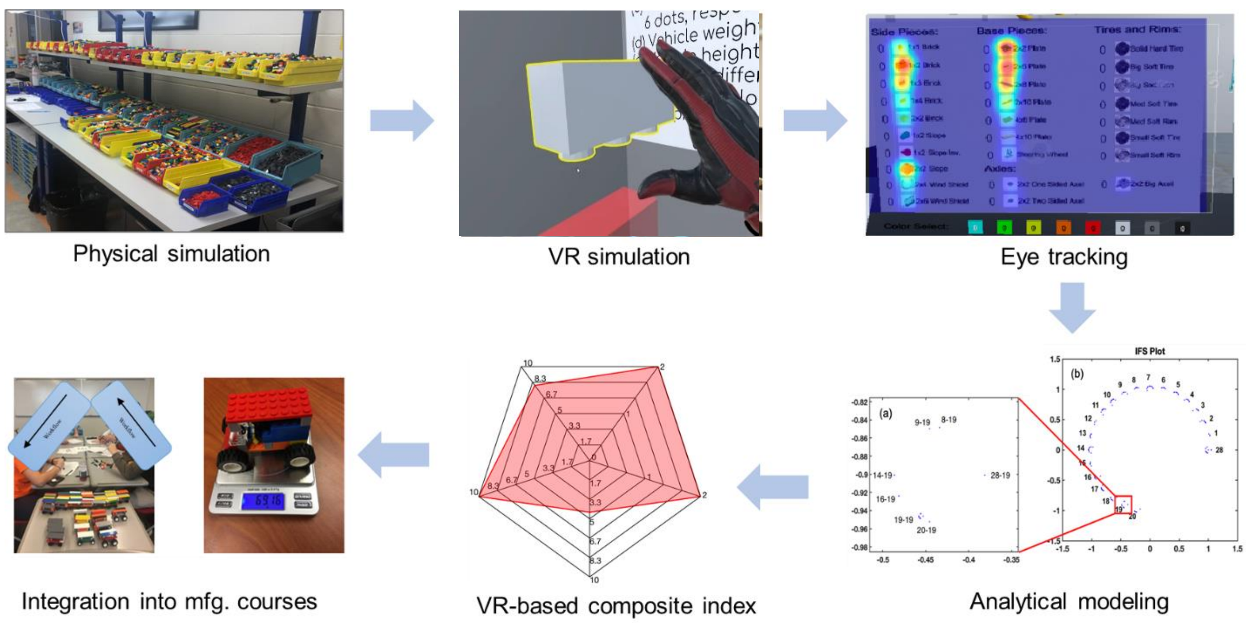


Figure 1. Research methodology.

3.1 VR Simulation of Learning Factory

In this research, a VR learning factory as shown in Figure 2 is developed to help engineering students understand manufacturing concepts and processes and gain hands-on training. The VR learning factory was built in the Unity game engine and worked with the HTC Vive VR headset, wireless controllers, and base stations for navigation and motion tracking [18]. Through the headset, students were presented with a virtual factory with a series of workstations. They were able to interact with the virtual environment and objects with wireless controllers.

To study the problem-solving of engineering students, we invited them to complete some assembly tasks. Assembly tasks given to students involved the assembly of car toys according to a set of customer requirements as shown in Figure 3. Students needed to minimize the total cost of car toy assembly while satisfying customer requirements. Hence, the assembly task consists of four main functions: design, sourcing, manufacturing, and inspection.

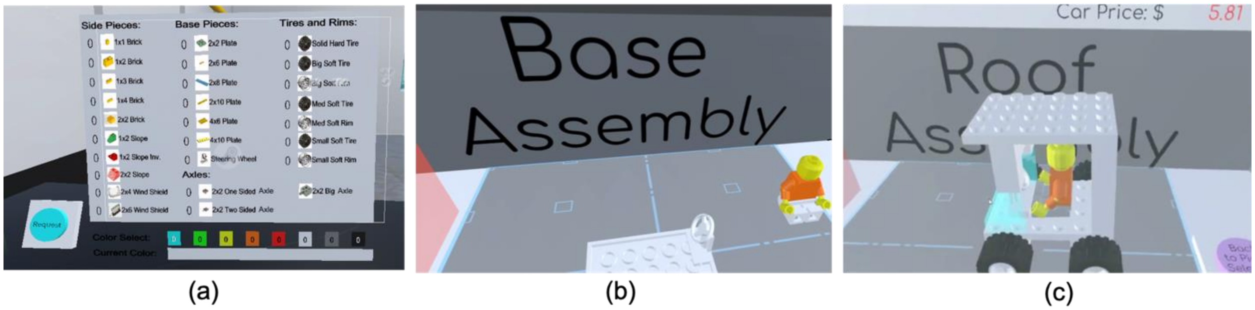


Figure 2. Workstations in VR learning factory: (a) component selection station; (b) base station; (c) roof station.

Car Option #1
(a) Vehicle must have four tires (with axles), windshield, steering wheel, and roof.
(b) All tires must be medium soft.
(c) Vehicle base width and length are 4 dots and 8 dots, respectively.
(d) Vehicle weight between 30 and 40 grams.
(e) Vehicle height must fit a sitting driver.
(f) Maximum different colors of the car is 6 (including color of tires and steering).
(g) Car price is $10.

Car Option #2
(a) Vehicle must have four tires (with axles), windshield, steering wheel, and roof.
(b) All tires must be small soft.
(c) Vehicle base width and length are 4 dots and 6 dots, respectively.
(d) Vehicle weight between 20 and 30 grams.
(e) Vehicle height must fit a sitting driver.
(f) Maximum different colors of the car is 5 (including color of tires and steering).
(g) Car price is $9.

Car Option #3
(a) Vehicle must have four tires (with axles), windshield, steering wheel, and roof.
(b) All tires must be large soft.
(c) Vehicle base width and length are 6 dots and 8 dots, respectively.
(d) Vehicle weight between 55 and 70 grams.
(e) Vehicle height must fit a sitting driver.
(f) Maximum different colors of the car is 7 (including color of tires and steering).
(g) Car price is $25.

Car Option #4
(a) Vehicle must have four tires (with axles), windshield, steering wheel, and roof.
(b) All tires must be medium hard.
(c) Vehicle base width and length are 4 dots and 10 dots, respectively.
(d) Vehicle weight between 30 and 35 grams.
(e) Vehicle height must fit a sitting driver.
(f) Maximum different colors of the car is 6 (including color of tires and steering).
(g) Car price is $7.5.

Figure 3. Examples of customer requirements for the car toy assembly.

Once students entered the VR learning factory, audio instructions on how to interact with the virtual environment were presented to them. After learning about the instructions, students could press a button to start the car toy assembly. There are seven workstations in the VR learning factory. The requirement station is the first workstation where students were shown a set of customer requirements (see Figure 3). After understanding the customer requirements, students moved to a component selection station (see Figure 2 (a)) and selected components by pointing at them and pressing a button on the wireless controller. There are 8 colors to be selected for each component. Then, students could complete the assembly process by assembling base, axle, tire and rim, front and trunk, windshield, sides, and roof in subsequent workstations as shown in Figure 4. Students could switch between seven workstations during the assembly process.

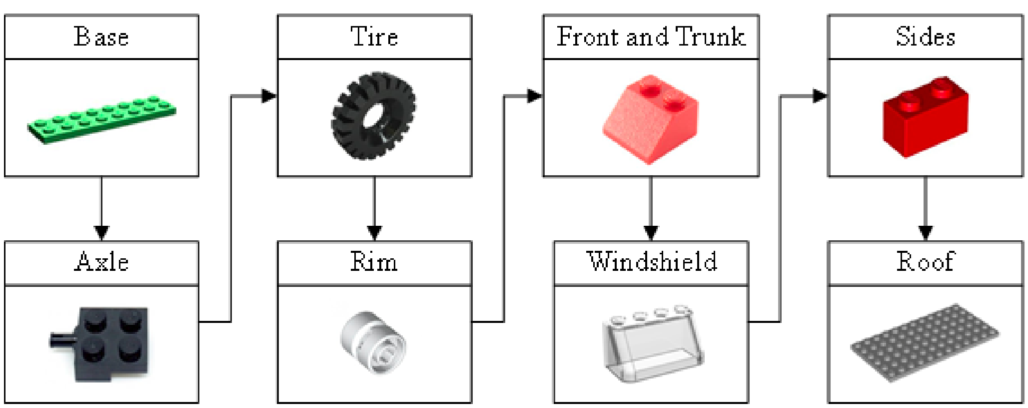


Figure 4. Processes for car toy assembly [19].

Eye-movement patterns including locations and number of fixations, saccades, and students' choices of components were recorded along the assembly process. Data-driven models are incorporated with eye-movement patterns to analyze students' problem-solving skills. For example, problem-solving skills are measured by the extent to which the eye-movement patterns of engineering students are similar to the pattern of an SME, a person who will set the expert criterion for the car toy assembly process. In our case, the instructor who led the development of the manufacturing simulations serves as SME.

3.2 Mean Squared Error for Eye Gaze Heatmap Comparison

Eye-tracking data generate compelling visualizations that are useful for the study of problem-solving. An eye gaze heatmap, as one of the visualizations, is developed for each student and the SME based on the number of fixations that one looks at components in the component selection station. As shown in Figure 5, the red color represents a relatively large number of fixations, while the blue color represents a relatively small number of fixations.

(a) Eye gaze heatmap of a student (b) Eye gaze heatmap of the SME

Figure 5. Eye gaze heatmaps developed based on the number of fixations on each component for every student and the SME. The red (or blue) color represents a relatively large (or small) number of fixations. (a) the eye gaze heatmap of a student; (b) the eye gaze heatmap of an SME.

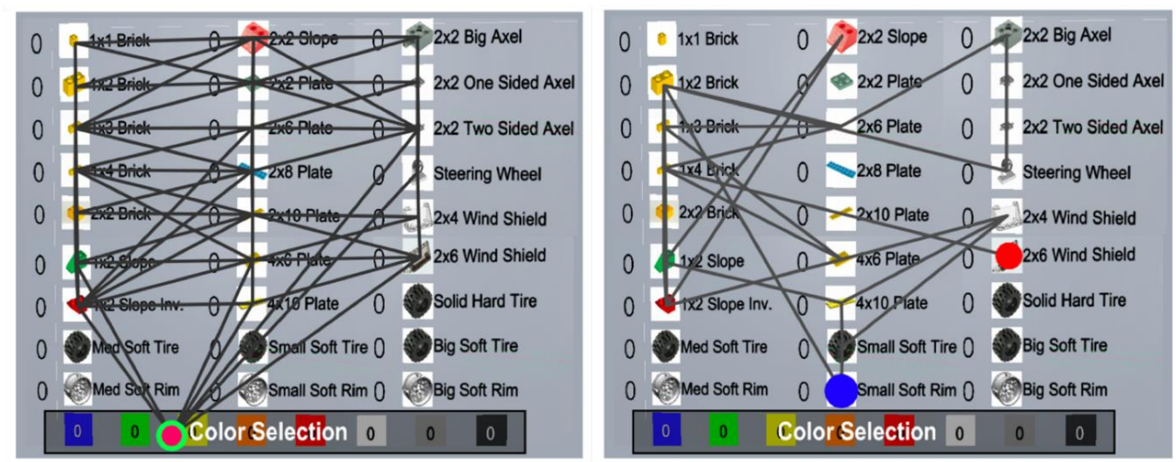
The comparison of eye gaze heatmaps between a student and the SME serves as one of the measures of engineering problem-solving skills. Mean squared error (MSE) is widely used for image comparison [20]. We use the eye gaze heatmap of an SME as the golden standard and compute MSE of all pixels on eye gaze heatmaps for each student in terms of RGB color as:

$$MSE = \frac{1}{M \times N \times 3} \sum_{m=1}^{M} \sum_{n=1}^{N} [(R_{mn} - R'_{mn})^2 + (G_{mn} - G'_{mn})^2 + (B_{mn} - B'_{mn})^2]$$

where M is the number of pixels along the horizontal axis, N is the number of pixels on the vertical axis, 3 is the chromaticity number in an RGB color which are red, green, and blue, R_{mn}, G_{mn}, and B_{mn} are the RGB color of each pixel on a student's heatmap, R'_{mn}, G'_{mn}, and B'_{mn} are the RGB color of each pixel on the SME's heatmap. Examples of RGB colors of two pixels are as shown in Figure 5. MSE of the student in Figure 5 (a) is 5.56.

3.3 Heterogeneous Recurrence Analysis of Scan Path and Pick Path

A scan path and a pick path are generated based on the eye-tracking data of each student or the SME as shown in Figure 6. A scan path provides the path that a student or the SME scans as they view the component selection board. As shown in Figure 6 (a), the green dot represents the starting point where the student starts to scan, while the red dot is the endpoint of the scan path. On the other hand, a pick path is an ordered set of selected components. Similarly, in Figure 6 (b), blue dot and red dot represent a starting point and an endpoint of the pick path, respectively.



(a) Scan path of a student (b) Pick path of a student

Figure 6. Scan path and pick path of a student: (a) scan path. Green and red dots represent starting and endpoints of the scan path, respectively; (b) pick path. Blue and red dots are starting and endpoints of the pick path, respectively.

Figure 7. 28 states on the component selection board.

The selection board in the component selection station is divided into 28 states, that is, each component represents a state as shown in Figure 7. A unique value of categorical variable k is assigned to each state $s(n)$, $k \in \{1, 2, \ldots, K\}$. $K = 28$ in this case. We obtain a sequence of categorical variables as one views the selection board.

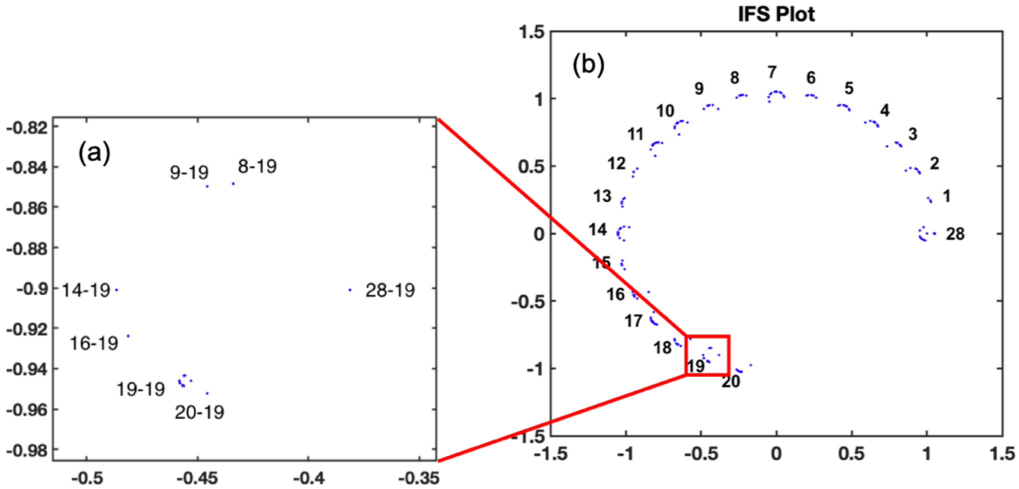


Figure 8. IFS plot of the scan path in Figure 6 (a).

In this research, an iteration function system (IFS) is introduced to represent heterogeneous recurrences of the sequence of categorical variables [21] [22]. IFS maps each state $s(n)$ to a point $[c_x(n), c_y(n)]$ in the 2D coordinate system as:

$$s(n) \rightarrow k \in \{1,2,\ldots,K\}$$

$$\begin{bmatrix} c_x(n) \\ c_y(n) \end{bmatrix} = \phi\left(k, \begin{bmatrix} c_x(n-1) \\ c_y(n-1) \end{bmatrix}\right) = \begin{bmatrix} \alpha & 0 \\ 0 & \alpha \end{bmatrix} \begin{bmatrix} c_x(n-1) \\ c_y(n-1) \end{bmatrix} + \begin{bmatrix} cos\,(k \times \frac{2\pi}{K}) \\ sin\,(k \times \frac{2\pi}{K}) \end{bmatrix}$$

where $\begin{bmatrix} c_x(0) \\ c_y(0) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$, α is a control parameter that prevents overlaps of two states in the 2D graph. Figure 8 shows the recurrences of 28 states in the scan path of Figure 6 (a). This contractive mapping clusters all the states with the same categorical variable k at local regions in the 2D graph. State 21, 22, 23, 24, 25, 26, and 27 are missing in Figure 8 because the numbers of fixations in these 7 states are 0, that is, the student did not look at components in 7 states. The zoomed-in Figure 8 represents transition sequences from all states to State 19. Note that transitions from State 1~7, 10~13, 15, 17, 18, 21~27 to State 19 are missing because the transition probabilities from these states to State 19 are zeros.

We denote clustered states as heterogeneous recurrence sets, i.e., $W_{k_1,k_2,\ldots,k_t} = \{\phi(k_1|k_2,\ldots,k_t): s(n) \rightarrow k_1, s(n-1) \rightarrow k_2, \ldots, s(n-t+1) \rightarrow k_t\}$, $k_1, k_2, \ldots, k_t \in \{1,2,\ldots,K\}$. Furthermore, we extract 3 quantifiers, i.e., heterogeneous recurrence rate (HRR), heterogeneous mean (HMean), and heterogeneous entropy (HENT) from the heterogeneous recurrence set $W_{k_1,k_2,\ldots,k_t}$ [23]. 3 heterogeneous recurrence quantifiers are defined based on the recurrence set $W_{k_1,k_2,\ldots,k_t}$.

HRR measures the percentage of recurrences within the set $W_{k_1,k_2,\ldots,k_t}$:

$$HRR = \left(\frac{\overline{\overline{W}}_{k_1,k_2,\ldots,k_t}}{N}\right)^2$$

where $\overline{\overline{W}}_{k_1,k_2,\ldots,k_t}$ denotes the cardinality of set $W_{k_1,k_2,\ldots,k_t}$, N is the total number of states in the state transition process.

Recurrence set $W_{k_1,k_2,\ldots,k_t}$ involves the same t-state sequence that is clustered at local regions in Figure 8. But addresses of t-state sequences in the set $W_{k_1,k_2,\ldots,k_t}$ are not exactly the same and are distributed in the local region. Thus, a distance matrix in the set is computed as:

$$D_{k_1,k_2,\ldots,k_t}(i,j) = \|\phi^i - \phi^j\|$$
$$\phi^i, \phi^j \in W_{k_1,k_2,\ldots,k_t}; \quad i,j = 1,2,\ldots,\overline{\overline{W}}; \quad i < j$$

where ϕ^i *and* ϕ^j are the *ith and jth* elements in the set $W_{k_1,k_2,\ldots,k_t}$. **HMean** is defined as the average distance of $D_{k_1,k_2,\ldots,k_t}$ to measure the average distance among states in the set $W_{k_1,k_2,\ldots,k_t}$:

$$HMean = \frac{2}{\overline{\overline{W}}(\overline{\overline{W}}-1)} \sum_{i=1}^{\overline{\overline{W}}} \sum_{j=i+1}^{\overline{\overline{W}}} D_{k_1,k_2,\ldots,k_t}(i,j)$$

The distance matrix $D_{k_1,k_2,\ldots,k_t}(i,j)$ is divided into B equal bins from 0 to max (D) and the probability is computed as:

$$p(b) = \frac{1}{\overline{\overline{W}}(\overline{\overline{W}}-1)} \# \left\{\frac{b-1}{B}\max(D) < D_{k_1,k_2,\ldots,k_t}(i,j) \le \frac{b}{B}\max(D)\right\}, \qquad b = 1,2,\ldots,B$$

HENT is defined as the Shannon entropy of the probability distribution of $D_{k_1,k_2,\ldots,k_t}(i,j)$ and describes the uncertainty in the recurrence of a t-state sequence:

$$HENT = -\sum_{b=1}^{B} p(b)\ln p(b)$$

4. Experimental Results

There were 25 participants including 24 students and 1 SME in the experiment. All 24 students were undergraduate engineering students. The average age was around 18. We recorded their eye-tracking data while assembling car toys in the VR learning factory. A synthesized quantifier was developed to combine 7 quantifiers extracted from eye-tracking data, i.e., MSE of heatmap, HRRs, HENTs, and HMeans of scan path and pick path. Meanwhile, to validate the effectiveness of the synthesized quantifier in measuring problem-solving skills, a VR-based composite index was designed to serve as the ground truth of students' assembly performance in the VR learning factory. The protocol for the simulation experiments was reviewed and approved by the university's Office for Research Protections (IRB #: STUDY00009232).

4.1 VR-based Composite Index

The VR-based composite index is formulated based on scores of cycle time, number of station switches, weight, price, and quality of the car toy. The highest score of car toy quality is 10. Starting from 10 points, each violation of customer requirement deducts 1 point from 10 points. For example, if a student does not assemble small soft tires, the student will lose 1 point and the score of car toy quality will be 9. A car toy obtains a score of 2 for its weight or price when the weight or price requirement is satisfied, otherwise, the score for weight or price is 1. A long cycle time or a large number of station switches usually results in unsatisfactory assembly performance. Therefore, scores of the cycle time and the number of station switches are formulated according to the reverse scaling. Scores of the cycle time and the number of station switches are formulated as:

$$\mathrm{Time\ Score_l} = \frac{\max(\mathbf{CT}) - \mathrm{CT_l}}{\max(\mathbf{CT}) - \min(\mathbf{CT})} \times 10$$

$$\mathrm{Switch\ Score_l} = \frac{\max(\mathbf{nSwitch}) - \mathrm{nSwitch_l}}{\max(\mathbf{nSwitch}) - \min(\mathbf{nSwitch})} \times 10$$

where $\mathrm{Time\ Score_l}$ and $\mathrm{Switch\ Score_l}$ denote scores of the cycle time and the number of station switches of lth participant, $\mathrm{l} = 1, 2, \ldots, \mathrm{L}$, $\mathbf{CT}$ is the cycle time set $\{\mathrm{CT_1}, \mathrm{CT_2}, \ldots, \mathrm{CT_L}\}$, $\mathbf{nSwitch}$ is the set of numbers of station switches $\{\mathrm{nSwitch_1}, \mathrm{nSwitch_2}, \ldots, \mathrm{nSwitch_L}\}$.

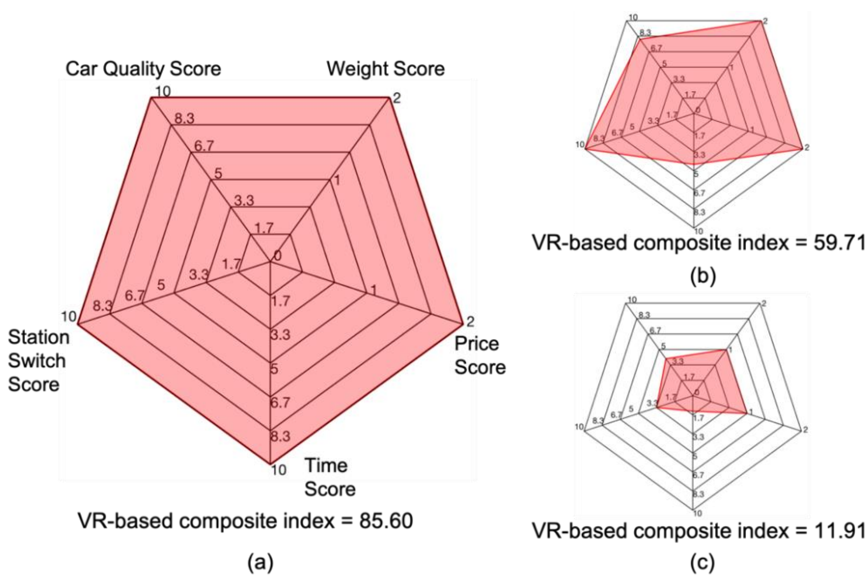


Figure 9. VR-based composite index represented by the red area in each spider chart which involves cycle time, the number of station switches, price, weight, and quality of the car toy. (a) VR-based composite index of SME; (b) an example of high VR-based composite index; (c) an example of low VR-based composite index.

Red areas in spider charts as shown in Figure 9 are values of VR-based composite indices. The highest VR-based composite index is 85.60 and belongs to the SME. This is because SME has full scores on all 5 axes. Examples of high and low VR-based composite indices are demonstrated in Figure 9 (b) and (c), respectively.

4.2 Synthesized Quantifier

In the design of synthesized quantifier, we first compute correlation coefficients between VR-based composite index and seven quantifiers which are summarized in Table 1. According to the correlation coefficients, MSE of heatmaps, HENT and HMean of scan path, HENT and HMean of pick path have negative correlations with VR-based composite index, which suggests the assembly performance decreases as these 5 quantifiers increase; HRR of scan path and HRR of pick path have positive correlations with VR-based composite index, suggesting larger values of these 2 quantifiers represent a better assembly performance. Therefore, HRR of scan path and HRR of pick path are normally scaled to range [0, 6], while MSE of heatmaps, HENT and HMean of scan path, HENT and HMean of pick path are reversely scaled to [0, 6].

Table 1. Correlation coefficients between VR-based composite index and the seven quantifiers.

	MSE of heatmap	Scan Path			Pick Path		
		HRR	HENT	HMean	HRR	HENT	HMean
Correlation Coefficient between VR-based Composite Index and Each Quantifier	-0.34	0.13	-0.57	-0.07	0.08	-0.41	-0.50

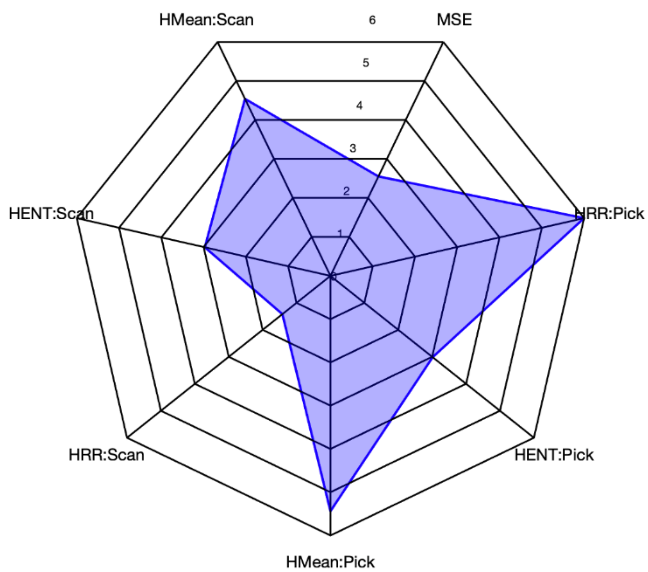


Figure 10. Synthesized quantifier represented by the blue area in the spider chart which combines MSE of heatmap, HRRs, HENTs, and HMeans of scan path and pick path.

A blue spider chart is designed to combine 7 quantifiers including MSE of heatmap, HRRs, HENTs, and HMeans of scan path and pick path as shown in Figure 10. The blue area in the spider chart is the value of synthesized quantifier. Further, the correlation coefficient between

VR-based composite indices and synthesized quantifiers of all 25 participants is computed as 0.56. It is noted that the upper bound of this correlation coefficient for a 99% confidence interval is 0.83.

4.3 Insights from the Analysis

According to the interpretation of correlation coefficients [24], a correlation coefficient of 0.56 with a 99% confidence interval upper bound of 0.83 demonstrates there is a strong correlation between the synthesized quantifier and VR-based composite index, that is, the proposed synthesized quantifier is effective to quantify students' engineering problem-solving skills in the VR learning factory. There might also be a potential nonlinear correlation between the synthesized quantifier and composite index which needs further investigation in the future work. On the other hand, this VR learning factory provides an advantageous environment for engineering students to enhance their problem-solving skills. For example, students can learn which are the necessary components they need to focus on and how to optimize the assembly process by observing an SME's behavior.

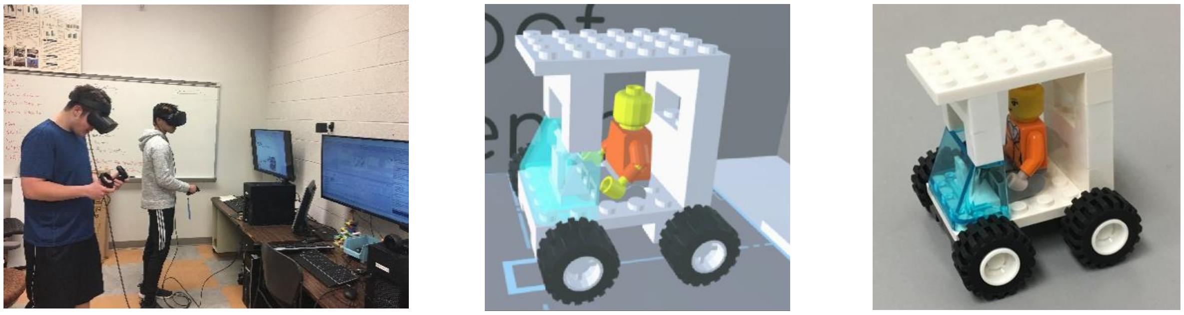
5. Integration into Manufacturing Courses

5.1 Laboratory Demonstration

The laboratory demonstration is a recognized technique in engineering education as it enhances the students' practical knowledge and allows students to investigate and solve real-world engineering problems [25]. VR learning factory, as a flexible tool that can provide state-of-the-art manufacturing systems and technologies as well as hands-on experiences to students, is imperative to be integrated into manufacturing curriculums. The availability of VR learning factory provides a new immersive environment to promote critical thinking, creativity, and collaborations among students. The proposed VR learning factory has been integrated into an undergraduate manufacturing systems course offered to Industrial Engineering students. Hands-on labs on both physical and VR simulations were developed. Figure 11 shows sample pictures from the physical simulation activities. Figure 12 shows sample pictures from the VR simulations.

(a) (b) (c)

Figure 11. Sample pictures from the physical simulations: (a) student participants using physical simulation to complete the production process, (b) inspection, (c) finished goods inventory [18].



(a) (b) (c)

Figure 12. Sample pictures from the simulations: (a) student participants using VR simulation, (b) sample car toy from the VR simulation, (c) sample car toy from the physical simulation [19].

5.2 Engineering Examination

Written exams are commonly used in manufacturing curriculums to test students' knowledge of manufacturing concepts and their ability to solve problems. However, good grades in exams do not sufficiently show if students have acquired manufacturing knowledge, because current exams usually test memory more than students' skills in solving real-world problems. Therefore, it is preferable to incorporate a VR learning factory with eye-tracking data analytics in the examination of manufacturing curriculums. For instance, an assessment can ask students to complete a certain project in a VR learning factory while at the same time recording their eye-tracking data working on the project. Evaluations can be based on the students' problem-solving performance in the project which is measured by the VR-based composite index as well as results of eye-tracking data analysis, that is, the synthesized quantifier developed in this research, as eye-tracking data are useful to reveal cognitive processes while students solving problems. Manufacturing knowledge questions can also be incorporated into the VR simulations and students can be asked to answer these questions in the VR environment once they finish the simulation activity.

6. Future Plans

In this research, the VR learning factory is designed mainly for a single player to gain hands-on manufacturing training. The single player simulation represents the craft manufacturing paradigm in which skilled workers, using general-purpose machines, make exactly the product the customer paid for; one at a time. Future work will focus on developing a VR learning factory that expands the VR simulations to other manufacturing paradigms and provide hands-on training for multiplayers as shown in Figure 13. The multiplayer VR learning factory comes with complex processes in 5 paradigms of advanced manufacturing: craft production, mass production, lean manufacturing, mass customization, and personalized production. Moreover, digital twins will be integrated with the multiplayer VR factory. This VR learning factory is composed of six rooms, one for each manufacturing paradigm and one for the inventory of products. The VR learning factory is aimed at enhancing advanced manufacturing training and facilitating collaborations through a shared visualization for both students and practitioners. Furthermore, eye-tracking sensing technology and artificial intelligence (AI) will be utilized for the data collection and modeling of users' behavior. The multiplayer VR learning factory will also allow for studying communication and teamwork in virtual teams as well as how students solve problems collaboratively.

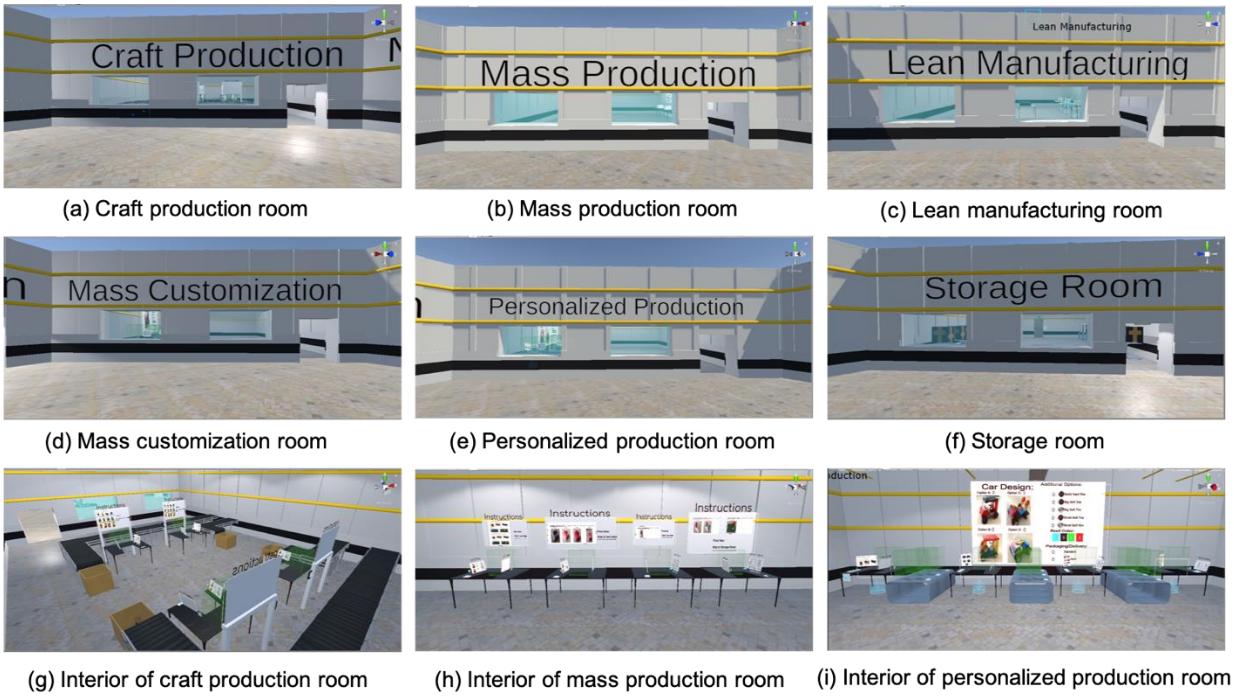


Figure 13. Snapshots of multiplayer VR learning factory for advanced manufacturing.

7. Conclusions

In this research, we developed a VR learning factory to mimic physical learning factories. Further, data-driven models are integrated with eye-tracking sensing to evaluate and enhance problem-solving skills of engineering students in a VR learning factory. First, a single-player learning factory is simulated in a VR game environment. Second, engineering students are asked to assemble car toys that satisfy customer requirements in the virtual environment. In the meantime, their eye-tracking data are recorded during the assembly process. Third, we developed data-driven models to analyze the eye-tracking data of students, thereby evaluating and enhancing their problem-solving skills when facing real-world engineering problems.

Experimental results showed that the proposed synthesized quantifier is effective to quantify problem-solving skills of engineering students due to its strong correlation with VR-based composite index which serves as the ground truth of students' assembly performance. The synthesized quantifier has strong potentials to be incorporated into engineering examinations as it is useful to reveal cognitive processes while students solving problems. Also, the VR learning factory can be utilized in the laboratory demonstration of manufacturing curriculums because it is flexible to provide hands-on training to students in the state-of-the-art manufacturing systems and technologies. The shared visualization in VR environment can facilitate collaborations among students.

Built upon the single-player VR learning factory, our future work will focus on the design of a multiplayer VR learning factory. The multiplayer VR learning factory is aimed at enhancing advanced manufacturing training and facilitating collaborations for both students and practitioners. The richness of the collected sensing data from students allows for the modeling of human behavior through machine learning techniques, and enables us to discover common trends in the students' learning and problem-solving process.

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