

The 15<sup>th</sup> International Scientific Conference  
eLearning and Software for Education  
Bucharest, April 11-12, 2019  
10.12753/2066-026X-19-007

**Improving Training Methods for Industry Workers through AI Assisted Multi-Stage  
Virtual Reality Simulations**

Alexandru BUTEAN, PhD., Marco Leon OLESCU, Nicolae Adrian TOCU, Adrian FLOREA, PhD.  
University "Lucian Blaga" of Sibiu, Faculty of Engineering, Department of Computer Science and Electrical Engineering  
10, Victoriei Bd., Sibiu, 550024, România  
alexandru.butean@ulbsibiu.ro, marco.olescu@ulbsibiu.ro, nicolae.tocu@ulbsibiu.ro, adrian.florea@ulbsibiu.ro

***Abstract:** For industry workers in the manufacturing space, the most time-consuming and less-productive process is represented by the multitude of training stages. For each new process / module / change in the manufacturing flow, there is a need for another customized training stage. For demanding industries (automotive, toys factories, household appliances, etc.) where customization is the key to sell more products, the time spent for preparing, designing and training people for new scenarios represents an important parameter that influences the production cycle efficiency. The current paper presents a solution to improve the measured performance on a new custom given task added to an existing scenario, using a multi-stage virtual reality (VR) simulator. The simulator acts as a digital twin for a physical testbed that offers 20+ parts to build the end product. To prove the performance of the solution, the first experiment uses a realistic multi-layered toy car as the end product. Both activities (real and virtual) are favoring the exploration of the building process, allowing the user (trainee) to discover multiple solutions that should lead to the same final result. The course of actions is supervised by an adaptive AI algorithm that compares the progress made by previous attempts (successful or not) with the ongoing attempt of a user and offers real-time guidance. Aside from using a gamified lego-like experience, the described approach contributes to the training process by offering personalized contextual suggestions, advices and tips. The article contains a serious state of the art study, current version specifications and objectives, details regarding the architecture of the solution, development components, results, comparative experimental tests and conclusions.*

***Keywords:** Industry 4.0; Virtual Reality; Training; Artificial Intelligence.*

## **I. INTRODUCTION**

### **1.1 Trends**

Digitalization creates disruptive trends in many societal and industry areas. Industry 4.0 concepts are no longer limited to theoretical architectures, instead they are already implemented in many use-cases [4]. Cyber-physical-social systems are evolving at a fast pace, making space for disruptive technologies that foster innovation and have the capacity to better reintegrate the human in the loop [6]. To achieve sustainability, every few months, modern manufacturing companies, require a new dynamic set of skills. Producers indicate that they can't keep up with this ascending trend, while almost 90 million people could lose their (semi) manual jobs, being replaced with fully automated machines [5]. For this reason, the manufacturing industry needs to come up with fast training programs to educate the current and future employees and offer them new professional competencies and skills to create and apply design tools in both digital and physical environments [1].

## **1.2 Paper scope**

The presented progress is part of series of experiments that will be used in the development of a complex cyber-physical-social-system, a self-configuring and dynamic industrial training space that aims to overcome the current industry workforce challenges. The overall objective of this prototype is to find a new way of organizing task-specific trainings, by implementing a 3-step training process for manufacturing industry employees:

- A. introduction - a trainee will receive text-based information about a process that he needs to follow in order to build a complex product;
- B. virtual training - the user will first enter a virtual reality space where he is experimenting a progressive training to familiarize with a specific manufacturing scenario;
- C. real process - the same person is now facing the same problems in the real world with a replica model of the previously experimented product.

This article covers only one of the above stages: the virtual training stage (B). All other stages (A, C) have a low priority and will be detailed in other materials. The scope of the current paper is to present the results of an ongoing work that demonstrates how automation can improve performance efficiency of human workers, by including an adaptive AI (Artificial Intelligence) that will supervise the training process, compute performance scores and suggest advice along the way. The final purpose will be to compare a VR (virtual reality) space and a real assembly scenario in order to understand how the immersive training environment is improving the learning curve.

Major industrial facilities usually have more headquarters spread across the globe and multiple use-cases to study, asses and update before introducing them into production. By creating a training tool that facilitates the knowledge transfer remotely, it enables employees to have shorter real training sessions and offers a virtual guiding tutor for experimental and educational purposes. For now, our current approach focuses on how automation can help in certain domain-knowledge tasks in order to accelerate the training process for new tasks / jobs that require manipulation of simple parts.

After this brief introduction chapter, the rest of the material is organized in a traditional manner. Chapter II presents a relevant state of the art study where several related work initiatives are describing the most influential fields where AI algorithms or virtual environments have been used to improve the quality of learning. Chapter III explains the concept of the training scene, focusing on how the VR scene and the adaptive AI interact with the user. Chapter IV illustrates the experiments conducted using these training scenarios and some relevant results that describe how this unconventional training methodology can improve the quality of knowledge transfer. Finally, chapter V presents the conclusions, ongoing work and future improvements.

## **II. RELATED WORK**

### **2.1 Virtual Reality Simulator for Construction workers**

In specific workplaces, where there is a high risk of injuries, the real trainings have to be limited so that the user is always safe. By making use of a virtual reality simulator [3], the authors describe a training for construction workers which includes no limitations to what a user can or cannot do. The in a virtual simulator leaves plenty of space for experiments and forces the worker to pay attention to details. In this particular field, being able to involve the trainee in different situations that could happen on a real working site, can help the actual operator to have a better overall view of the task, possible outcomes, better knowledge of all the tools and processes and can therefore perform better in the real environment, while also knowing which actions can lead to dangerous events.

### **2.2 Virtual Reality Training of Hard and Soft Skills in Production**

In [2], the authors present a virtual reality training system for production workers, which covers hard skills for specific tasks (different manual operations) but also different soft skills needed in order to manage quality checking tools (Pareto diagrams, control charts etc.). The training includes a virtual reality teacher, different lessons with visual and audio support and different tests in order to

see whether the knowledge transfer can be improved, while also using fewer human resources. This solution is not only time efficient, but it seems that uses a very efficient human-centered methodology.

### 2.3 Study of self-avatar's influence on motor skills training in immersive virtual environments

Motor skills usually involve a lot of coordination and can be better learned through the user's embodiment and orientation. In [9], different hand representations were studied to see if any of these have a better influence over the knowledge transfer phenomena. After performing the same training on various representations, the users were asked to compare the virtual models with the real one, giving feedback on which method gave the best results. The study focuses on several KPI's: task completion time (ms), the accuracy of objects' placement (mm), and the number of errors (counted as objects dropped during trials). The presented experiment is applied on a pick and place motor task, but it could be applied to any task involving the training of a motor skill.

### 2.4 Mechanical assembly trainings through VR and AR

An approach [8] that is similar to ours is presented by combining virtual and augmented reality into a training session, in order to benefit from both technologies. By having a virtual reality scene, they created a cost-efficient environment where manufacturers can have specific trainings on assembling components. A great conclusion is that this training process has a lower knowledge transfer when using only the VR environment because it cannot mimic the exact climate of the real work. Here is where the augmented reality session comes in play, by allowing the trainee to assemble the real pieces, while also having special pattern indications on how to combine specific parts. By adding this stage, they managed to have a better transference phenomenon while also greater flexibility and efficient resource usage.

## III. TRAINING ENVIRONMENT

### 3.1 Objects and models

To evidenciate the planned architecture, we propose a classical VR implementation for a specific assembly task - a car made out of components. The initial scenario is meant to be useful and educational for the automotive industry and car service facilities. Originally, in the current stage, for experimental purposes the real objects were chosen to be made out of simple lego blocks (Figure 1) because they were very easy to understand and reproduce in a block based environment. The virtual objects from the VR environment represent a slightly more complex product (only design wise) but with the same structural parts of a car (figure 1).



Figure no. 1. Real world representation of a car made out of lego (left) and virtual model (right)

Both models (real lego car and virtual car) are mapped on a matrix structure that allows a 1-1 relation between a real world part and a virtual part. The colored virtual placeholders (figure 2) are evidientiated to show where and how the trainee should place specific car parts.

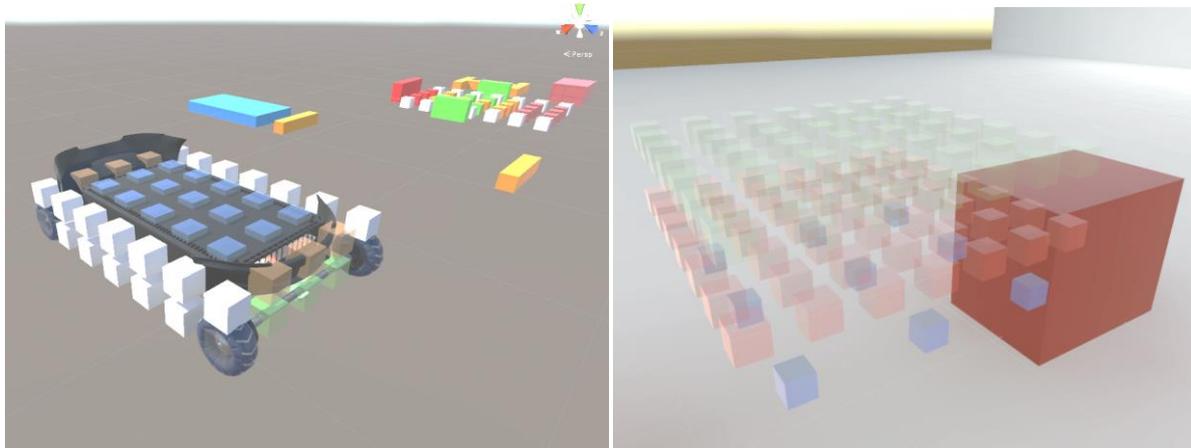


Figure no. 2. Example of the matrix structure with colored placeholders

### 3.2 Training Stage

The Unity platform was used for the creation of the training stage. The trainee can enter the immersive world using an Oculus Vive Headset and manipulate the objects using standard Oculus VR hand controllers.

To ensure a proper educational climate, the current training logic allows multiple session types, enabling the user to gradually perform various tasks, starting with several subassemblies, which have a low difficulty level (putting 2 wheels and axle), then working only on the first layer (wheels, axles and dial) and up to the final stage (assemble the whole car from beginning to end).

Each training stage contains the following components: an information panel, a table with the available parts for the specific stage and 3 layers made out of colliding cubes (first layer - 3x3, second layer 7x7, third layer 4x4). The cubes (figure 2) represent the placeholders where the trainee can put the pieces together.

For the assembling part, the trainee needs to pick up any piece from the table (Figure 3- left) and place it on one of the collider cubes, in any direction he wants. When a component hits one of the cubes, it will be placed in a certain position. We have created several layers of matrices, all of them having 3x3 colliding cubes, so that we can represent the whole car in a 3D environment. The current implementation is giving the user the freedom to have his own solution (he can start building the car with any given piece).

As there is only one final solution for a scene, an error checking algorithm (Figure 3 - right) is checking the colliders, telling the user whether or not the piece that he just placed is now in a correct position. This feature is giving the trainee a boost of confidence (seeing that he is on the right track) and an easy way to fix placement problems while trying to complete the 3D puzzle.

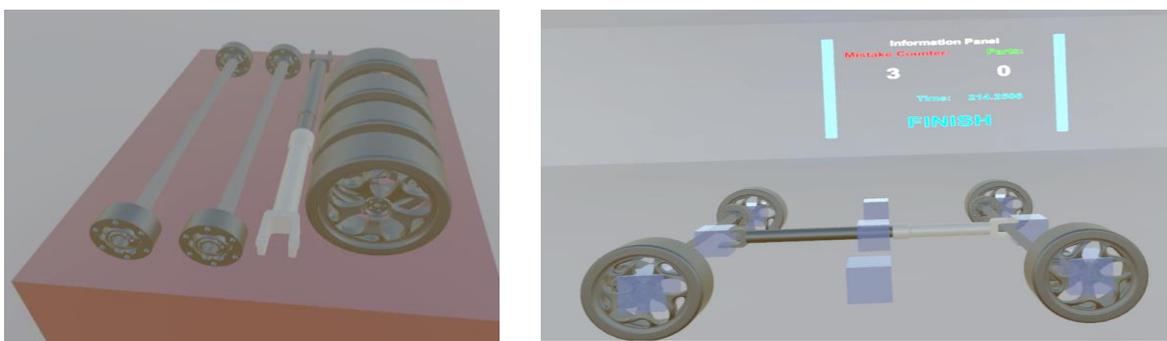


Figure no. 3. Table with available parts (left), information panel and completed layer one (left)

As soon as the trainee completes the training, the information panel will show the user how many mistakes has made during this trial and his timing. This information will be needed later on, as in order to make comparisons and see how each individual has performed on the VR task.

After the completion of the first scenario (wheels, axels and train), the trainee will go on and complete the other steps of the training until he finally manages to build the entire car. With the acquired knowledge in the virtual environment, the trained user can pursue the real life task.

The real model resembles a lot with the virtual one, but is not a 1:1 replica because we would like to see if the training has created flexible enough skills, allowing the trainee to adapt when there are some minor changes between the two models.

### 3.3 Artificial intelligence algorithm

During each training, the user will be supervised by an adaptive AI, which will try to help the user with suggestions related to an ongoing progress. At the beginning of each individual session, we will start a classic genetic algorithm [7] that has the task to complete the same assembly as the user.

In this first version the AI algorithm will only supervise the virtual training scene, but in the next versions we plan to integrate an object tracking mechanism using a RGBD camera and apply the same algorithm to be able to give feedback and suggestions also to the the real-world scenario.

A genetic algorithm was chosen in order to mimic the human learning process that is exploratory and often relies on try and error scenarios. The learning process of the algorithm is straightforward brute force, with no prior solution fed into the algorithm.

The architecture of the current algorithm is the one of a general genetic algorithm (figure 4), with the adapted operators according to the current method requirements.

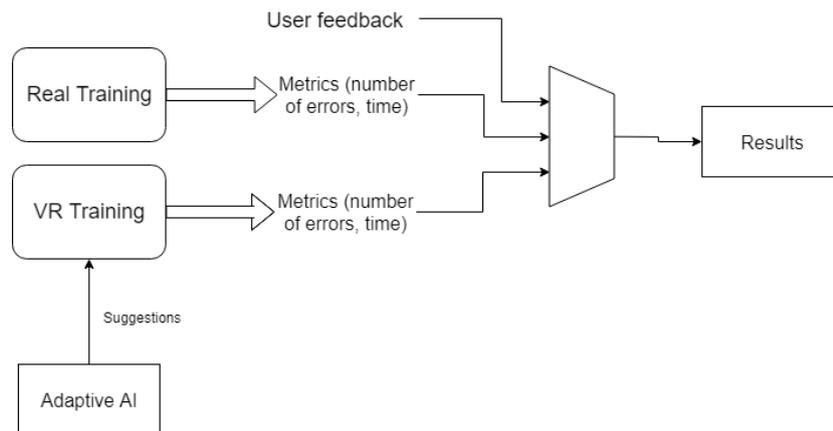


Figure no. 4. General architecture for genetic algorithms

A solution for the algorithm is defined as a 3 matrices (one for each layer: 3x3, 7x7, 4x4), where each element is represented by a number (which encodes one of the pieces). The fitness function for such a solution is the number of pieces that differ from the optimal solution (this function will have to be minimized). Regarding the genetic operators, we have chosen the following implementation steps:

- Selection of the parents for the population: For each iteration we sort ascendant the population based on fitness and we will keep half of the population with the lowest fitness for the next generation. The crossover and mutation will be applied on the rest (not-selected) of individuals to create new offspring.
- Crossover: two parents will be combined and we will use a 1 split point crossover for each layer: we will randomly choose a line in the matrix where we want to split and the child will get the first part (starting from the first line up until the chosen line) from the first parent and the second part from the second parent.
- Mutation: in this implementation for this operation, we chose to randomly change one value from each layer into another piece.

As a user progresses through the training, the algorithm counts every move and verifies if it is a good move or a bad move (the mistakes counter considers how many times the user has placed a certain piece in the wrong slot). Giving all this sequence of moves, we can check if the user needs help (more than 5 mistakes). This is where the AI comes into play. As soon as it observes that the user has made a big number of mistakes, the algorithm will suggest to the user where he needs to place one of his remaining pieces. Having all this information, the user is guided to move forward even if he does not perform well enough.

#### **IV. RESULTS FROM THE TESTING SESSIONS**

During the development stages and after the release of the alpha version we have conducted several tests to gather feedback, understand the usability issues and identify how is the method improving the classical approach. The final testing process involved 20 people of different ages, but with the same technical background (engineering students, professors, researchers). We've created two groups:

- one group - 10 people - they've interacted only with the real-life model and tried to assemble the car in a traditional way;
- the second group - 10 people - they've interacted first with the training system and after that with the real-life model.

The first group acted in a predictive manner, after 5 attempts (each of 3 minutes), only 6 people managed to build the car under 1 minute with a top score of 49.3 seconds.

The second group went through all the training stages. They started with layer 1 assembly training, all the way to the VR training with the whole car and the final test with real-life model. The participants in this group were allowed an extra 2 attempts to accommodate to the virtual reality environment. After a total of 7 attempts (each of 3 minutes), no participant finished under 1 minute but 5 participants were able to finish the VR final task (car assembly) under 2 minute. After going from the virtual environment to the real environment, after 5 attempts (each of 3 minutes), 8 people managed to build the car under 1 minute with a top score of 42.1 seconds. Regarding the AI intervention, we measured the total number of interventions per person during the training stage. The average number of interventions was 13, with many interventions in the initial stage when people were confused on how to use VR controls and less interventions after the first 5 attempts.

#### **V. CONCLUSIONS**

The current paper presented a method to improve the training methods for industry workers though AI assisted multi-stage VR training. For the first alpha version, the complexity was reduced to a simple car assembly use case. A car built from lego bricks has a digital-twin (identical in structure but slightly changed in design). The purpose of the application is to train people on the virtual model and then evaluate their skills on the real-world scenario.

The VR environment allows a gradual training process and prepares the user for the final assembly task. The process is gradual and exploratory and the user is allowed to place any part in any place, guided by several placeholders divided into 3 layers.

An AI algorithm was built using a classical genetic algorithm logic to solve the quest faster and supervise the training process while giving hints to those who make mistakes but want to move further.

A modest testing session with 2 groups of 10 people showed promising results and revealed the following interesting conclusions:

- the research on this study is still in the early stages and a flexible application can easily adapt to numerous assembly scenarios;
- even if the methods seem to work well on this reduced complexity use-case, we have to reiterate the fact that, there will always be the problem of creating an exact replica

of a real model: as many parameters or possibilities we include, a virtual scenario would not be able to mimic the real world, thus we accept that a trainee might have several adaptation issues when dealing with real world scenarios;

- a fundamental opinion after this current approach is that when it comes to using new technologies for any kind of task, the human acceptance level is low and it requires a longer period of time to adapt to each particular.

The research will continue with the plan to extend the current training scenarios by exploring the following areas:

- introduce another step (an augmented reality scenario) between the VR stage and the real assembly process, similar with the approach from [8];
- identify and assess a medical use case (elderly people [11], rehabilitation [10]) that uses the existing model as a starting point;
- integrate human perception sensors (pulse, eye tracking, etc) to build more complex profile that will enable us to have personalized suggestions and outputs for certain categories;
- perform a testing session with more than 100 industry workers, gather feedback, analyse the comparison training data and refine the system accordingly.

### Acknowledgements

This work is supported through the DiFiCIL project (contract no. 69/08.09.2016, ID P\_37\_771, web: <http://dificil.grants.ulbsibiu.ro>), co-funded by ERDF through the Competitiveness Operational Programme 2014-2020.

This work was partially developed under the ERASMUS+ KA2 project "THE FOF-DESIGNER: DIGITAL DESIGN SKILLS FOR FACTORIES OF THE FUTURE, financing contract no. 2018-2533 / 001-001, project number 601089-EPP-1-2018-1-RO-EPPKA2-KA", web: <http://www.digifof.org>.

### Reference Text and Citations

- [1] European Commission, Upskilling European Industry: New operational tools wanted, 2019, Last accessed Feb 2019 at <http://ec.europa.eu/social/main.jsp?catId=1224>.
- [2] Górski, Filip; Zawadzki, Przemysław; Buń, Paweł; Starzyńska, Beata; Virtual reality training of hard and soft skills in production, Proceedings of the 23rd International ACM Conference on 3D Web Technology, 2018, Article No. 33.
- [3] Hafsia, Mehdi; Monacelli, Eric; Martin, Hugo; Virtual Reality Simulator for Construction workers, Proceedings of the Virtual Reality International Conference - Laval Virtual, 2018 Article No. 11.
- [4] Liao, Yongxin; Deschamps, Fernando; Rocha Loures, Eduardo; Ramos, Luiz; Past, present and future of Industry 4.0 - a systematic literature review and research agenda proposal, International Journal of Production Research, 2017, Volume 55, Issue 12, 2017, pp. 3609-3629.
- [5] Mckinsey Global Institute; Jobs Lost, Jobs Gained: Workforce Transitions In A Time Of Automation, Mckinsey Reports, 2017, pp. 1-160.
- [6] Olguín, Manuel; Wang, Junjue; Satyanarayanan, Mahadev; Gross, James; EdgeDroid: An Experimental Approach to Benchmarking Human-in-the-Loop Applications, Proceedings of the 20th International Workshop on Mobile Computing Systems and Applications, 2019, pp. 93-98.
- [7] Pei, Min; Goodman, Erik; Punch, William; Ding, Ying; Genetic algorithms for classification and feature extraction. 2019, Last accessed Feb 2019 at <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.67.4377&rep=rep1&type=pdf>.
- [8] Peniche, Amaury; Diaz, Christian; Paramo, Gabriel; Trefftz, Helmuth; Combining Virtual and Augmented Reality to Improve the Mechanical Assembly Training Process in Manufacturing, Proceedings of the 6th WSEAS International Conference on Computer Engineering and Applications, 2012, pp. 292-297.
- [9] Ricca, Aylene; Chellali, Amine; Otmane, Samir; Study of self-avatar's influence on motor skills training in immersive virtual environments, Proceedings of the Virtual Reality International Conference - Laval Virtual, 2018, Article No. 15.
- [10] Surya Mohd Arip, Eza; Ismail, Waidah; Nordin, Md Jan; Radman, Abduljalil; Virtual reality rehabilitation for stroke patients, AIP Conference Proceedings, Volume 1905, Issue 1, 2017.
- [11] Taerel, Rares; Mocanu, Irina; Balan, Oana; Moldoveanu, Alin; Morar, Anca; Active gaming to promote physical activity for elderly people, 9th International Conference on Education and New Learning Technologies, 2017, pp. 1776-1781.