Virtual Reality for Emergency Healthcare Training

Peng Xia
Department of Computer Science
Auckland University of Technology
peterxianz@outlook.com

Ji Ruan
Department of Computer Science
Auckland University of Technology
jiruan@aut.ac.nz

David Parry
Department of Computer Science
Auckland University of Technology
dave.parry@aut.ac.nz

ABSTRACT

Given the rising trend of natural and technological disasters in recent years, the demands for emergency responders are on the rise. One main challenge is how to cost-effectively train emergency responders. In this research, we aim to explore of the usage of Virtual Reality (VR) technology in an emergency healthcare training setting. We start with the following two research questions: (1) how to implement the VR technology to be used in the emergency healthcare training; and (2) how to evaluate the effectiveness of our implementation. To address the question (1), we construct emergency healthcare workflows from reference sources, convert them into process diagrams, and develop a VR software that allows users to carry out the processes in a virtual environment. To address question (2), we design an experiment that collect participants' personal data (features such as Age, Technical Background etc.) and the performance data (such as timespan, moving distance, etc.) generated during the training sessions. Ten participants were recruited and each performed three training sessions. We evaluate the data collected and have the following two main conclusions based on the observation of ten participants: (a) despite the different personal features, the participants, after repeated trainings, can improve their performance with reduced timespan and moving distance; and (b) the Technical Background has the highest impact on the timespan initially and it is reduced most significantly after repeated trainings; meanwhile, the Prior VR Exp has the lowest impact on the timespan.

Keywords

Virtual Reality, Emergency Healthcare, Training, Workflow, Quantitative Research

INTRODUCTION

Given the rising trend of natural and technological disasters in the recent years (CRED 2016), the demands for emergency responders are on the rise. One main challenge is how to cost-effectively train emergency responders. Recent development of new digital technologies, especially Virtual Reality (VR), could provide a solution. VR technology has attracted a huge amount of interests in recent years due to the advancement of chip and display technology. The wide availability of consumer-level VR products (from companies such as SONY, HTC, Facebook, Samsung, etc.) provides low-cost solutions of experiencing VR, and hence is more accessible to the public. Compared with the old generation of VR technology, the developing and deploying costs of current VR technology are significantly decreased. Additionally, the current VR technology can bring a full-immersive and interactive experience to users, thus it can provide an ideal solution to simulate and solve specific problems. In this work, we aim to provide a solution of using VR technology to train emergency healthcare responders.

VR technology has been applied in improving healthcare and emergency response. *Some focus on specific healthcare and medical problem solving*, such as bleeding control (Khnapfel et al. 2000), stroke rehabilitation (Yamato et al. 2016; Hilton et al. 2011), treatment for patients with PTSD from the Iraq war (Rizzo et al. 2006), laparoscopic training and evaluation (Aggarwal et al. 2006; Larsen et al. 2009), and trauma healthcare telepresence (Soderholm et al. 2008). *Some focus on emergency response*, such as mining safety (Schofield 2009; Costa and Stelescu 2014; National Institute for Occupational Safety and Health Office for Mine Safety and Health Research Pittsburgh Research Laboratory 2000), nursing response in specific emergency situations (Kilmon et al. 2010), and industry safety (Bhide et al. 2015; Burke et al. 2006). *Others focus on healthcare education*. Izard developed a VR-based anatomy software which can be used to analyse and visualise the inner structures of human body (Izard 2016).

We notice that there are a few explorations of using VR technology to train specific emergency healthcare skills, but none of them attempted to train with the entire emergency healthcare workflow. Our work will fill the gap by an implementation of VR for an entire emergency healthcare workflow. Specifically, we address two research questions. *(1) How to implement the VR technology to emergency healthcare training?* We plan to construct an emergency healthcare workflow from reference sources, convert it into program-recognisable process diagrams, and develop a VR software that allows users to carry out the processes in a virtual environment. *(2) What approaches can be applied to evaluate the effectiveness of VR-based emergency healthcare training?* We will design an experiment that collects participants' personal data (features such as Age, Technical background etc.) and the performance data (such as timespan, avatar moving distance, etc.) generated during the training sessions. And we will recruit participants, conduct the experiment and evaluate the data collected.

The rest of the paper is organised as follows. We first give the methodology for emergency healthcare workflow formalisation, experiment design and VR software implementation. Then we show the preliminary results of ten participants on the experiment. Finally, we make the conclusion and discuss future work.

METHODOLOGY

In this section, we present the methodological details of our VR implementation. We first define the emergency healthcare workflow and convert it to process diagrams. We then build the process diagrams into our VR software. Finally, we create and perform experiments, and evaluate the experimental results.

Emergency Healthcare Workflow (EHW) and Process Diagrams

The Emergency Healthcare Workflow (EHW) is constructed based on various emergency healthcare training reference sources, e.g., St John's *How to assess a casualty*. We first separate the emergency healthcare procedures into three parts:

- *Initial Assessment* is to conduct a rapid assessment of the patient using methods such as consciousness level checking and body swiping. Also, some essential information relevant to injury cause is also acquired.
- *Secondary Assessment* is to conduct a checking process of soft tissue injuries. Once this assessment is finished, we expect that patient is allocated correctly to specific recovery position such as a recovery trolley or an emergency vehicle.
- *Ongoing Assessment* is to monitor the patient's conditions and is usually conducted by professional paramedics.

As we focus on training first responders (not professional paramedics), we will deal with the initial and secondary assessments only. The initial assessment has two major components: *Resuscitation and Primary Survey*, and *Secondary Survey*. The *Resuscitation and Primary Survey* uses a rapid assessment method called the ABCDEs (St John2013). Specifically, ABCDEs stands for *Airway maintenance cervical spine protection*, *Breathing and ventilation*, *Circulation with haemorrhage control*, *Disability neurological status* and *Exposure/Environmental control*, respectively. Each of the single term in ABCDEs represents a group of essential tasks to assess and maintain the baseline of vital signs. In Figure 1 (left), we specified the tasks of ABC. Each task can be further divided into subtasks. We formalise each subtask using a process diagram based on techniques from software engineering methodology. Furthermore, particular vital signs or event statuses in each task are properly defined as *Task Attributes*. The attributes will be involved while performing specific *procedures*. Each formalized subtask contains a group of procedures, some attributes, at least one input and one output. For the case of A, "Airway maintenance cervical spine protection", there are 6 subtasks and each subtask is further represented as a group of procedures. Figure 1 (right) shows the procedures for the second subtask, which intends to decide the level of consciousness for a patient by asking some questions and observing the feedback from those questions. First, the attribute "level of consciousness" is identified and the contents of this attribute include various states of consciousness (shown in rectangles with round corners) such as "normal consciousness", "confused'," and "delirious", etc. Then, different procedures (shown in diamond boxes) which may change the "level of consciousness" attribute are identified and connected. Finally, the output of this attribute will be recorded. In total, we identified 20 baseline tasks (T1-T20) for the EHW, for which the full details are omitted due to the space limit.

Experiment Design

One of the main advantages of VR technology is that different environments can be simulated just in software without the need to change hardware. So, we design two scenarios for emergency healthcare training. The first scenario is a car accident near the landmark Sky Tower in Auckland, as shown in Figure 2 (left). The second scenario is an earthquake incident in Christchurch, as shown in Figure 2 (right).

The first scenario is designed to help participants adapt to the VR training software and learn the EHW knowledge. We prepare two training sessions for the first scenario with 5-10 minutes' break in between. The second scenario is designed to test whether they would recall and adapt the knowledge learned from previous training sessions for the first scenario. The total estimated time for the first scenario training sessions is approximately 45-50 minutes, and that for the second scenario training session is approximately 20 minutes; the time gap between the first and second scenario sessions is about a week.

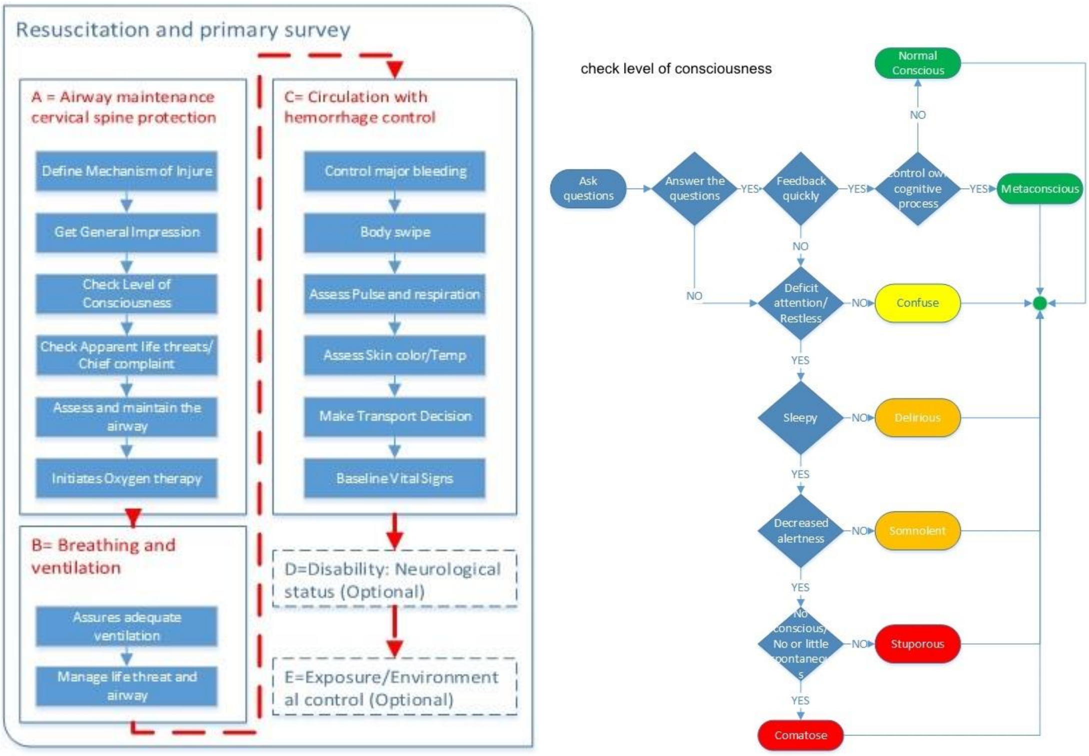

Figure 1. The Workflow of ABCDEs assessment and Procedures of "Check level of consciousness"

Figure 2. Bird's-eye View of Scenario 1 and 2 Environment

In this project, we choose Oculus VR hardware for its competitive price and well supported software development framework. There are three Oculus devices in use: Oculus Rift VR Headset, Oculus Sensors, and

Oculus touch controller. Additionally, we use two cameras to capture videos from participants for analysis purposes.

To achieve the best configuration required by VR sets, the minimal size of the room is set to be 40m². Figure 3 shows the experiment environment and equipments more precisely and the participants, also known as trainees in this research, are asked to wear the Oculus Rift headset and hold two Oculus controllers while performing tasks in our VR software. They need to perform the procedures within a circled *Performance Area* with a range of 3200mm diameter approximately. A larger space called the *Guardian Area* overlaps with this Performance Area, and there are no physical obstructions in these areas. If the participant's body moves out of the Performance Area or recording sensors start to lose tracking, the research staff will provide assistance. Three Oculus motion capture sensors are at the front-left, front-right and back-left positions respectively (seen as numbers 2, 3 and 6 in Figure 3). Those sensors will keep tracking constellations of IR LEDs from the headset and controllers and translate participant's movement and actions in the virtual environment. Two cameras are set at the front-central and either front-right or front-left position.

We use the quantitative research methodology to evaluate the use of VR in emergency healthcare training. Quantitative research is the systematic empirical investigation of observable phenomena via statistical, mathematical or computational techniques (Given2008). We notice that in (Aggarwal et al.2006), three main data items ("timespan", "distance" and "personal feature") are collected for evaluating the VR training effects. Our

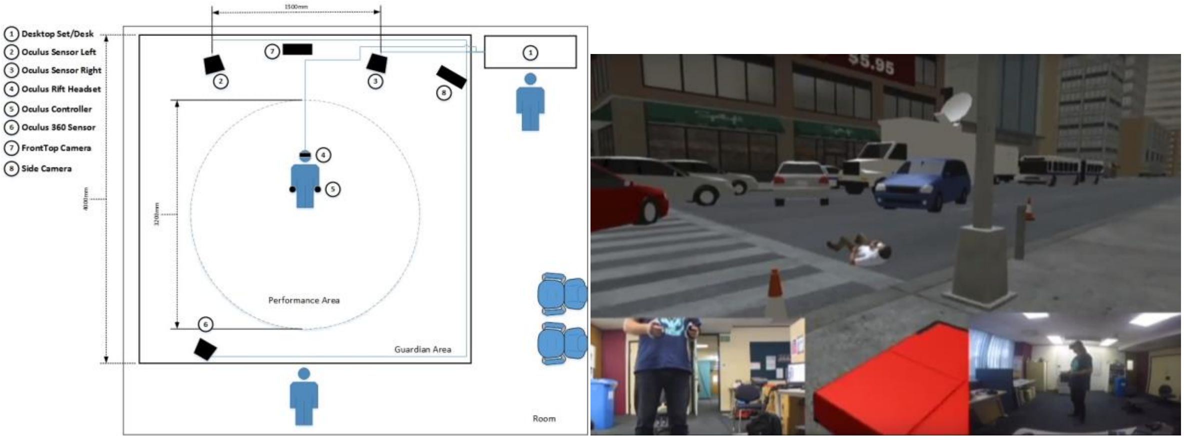

Figure 3. Experiment Environment Set Up and The Multi-view Screen

evaluation uses a similar approach and collects two kinds of data: *Personal Data* and *Performance Data*. The *Personal Data* is collected in the beginning of the experiment, and it includes a trainee's personal attributes such as age, technical background, and education background, etc. We want to explore how these personal attributes affect their performance. The *Performance Data* is collected during the experiment from the Oculus devices and the cameras by the VR software we developed. This data includes two main data formats, sensor data and media stream data. The sensor data includes various float numeric items which represent current states of the training session, such as the movement distance of the participant's virtual avatar, and left/right controllers, the time usage of each tasks and subtasks. The purposes of collecting media stream data is to assist us to analyse the participant's performing behaviours and record if any special actions are performed which could not be presented or reflected by the sensor data. The personal data and sensor data are stored in a MS-SQL-Server. The media stream data is stored in a dedicated external hard drive.

VR Software Implementation

We use an incremental build model as the main development methodology to conduct our progress and ensure the quality of the VR software. In this model (see Figure 4), the design, implementation, and test phases from the traditional waterfall model should be iterated incrementally until the software finally satisfies the requirements. One of the main advantages of this model is that, we can maximize the scales of the software with the addition of iterative qualities within a limited development period, and it also give us the flexibility to adjust the development progress and quickly responded to any problems as they occur.

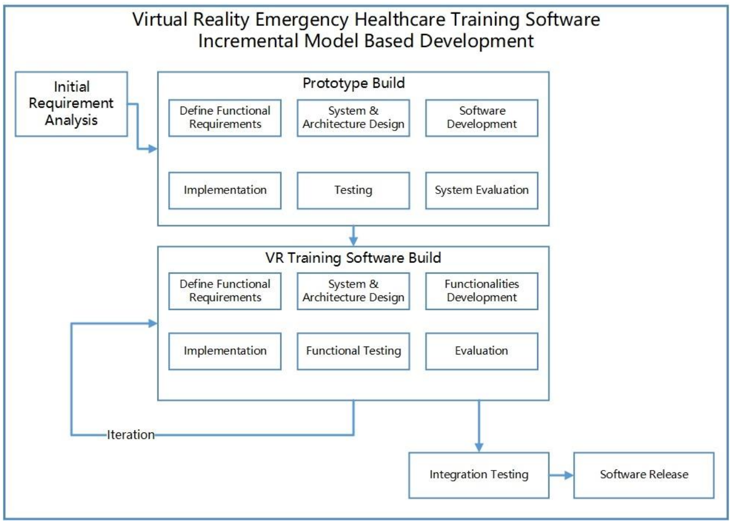

Figure 4. Incremental model for VR emergency healthcare training software

We first developed a prototype application to test which development techniques and platforms are suitable for this research project in the perspectives of learning and use difficulty, extensibility, stability, compatibility with commercial VR hardware, etc. We tested two most popular VR develop engines: Unity Engine and Unreal Engine. Based on reviews from (Amiel2015) and our own, we compared advantages and disadvantages of both engines and decided to use the Unity Engine due to its lower learning curve and the compatibility with C# Language and .Net Framework. We designed a lightweight system architecture with three major layers (from top to down): "Presentation Layer", in which we defined the components and objects responsible for managing all user-end interaction and visual presentation; "Logical Events Layer", in which we defined the components to control the event logic for the upper layer; and "Supporting Layer" which consists of core library and compilers. In parallel, we have a central controlling component called "Global Manager", which controls all task events, transmits data and variables between tasks, records the task status and performance data (sensor data). The purpose of designing this component is to keep the different layers independent and provides extensibility in future development. With the above architecture, we then mapped the EHW baseline tasks as major tasks in the VR software. We mapped the 20 EHW baseline task to 10 major tasks which contain 30 subtasks in total. Moreover, we included a tutorial task to get trainees familiar with essential interactions such as 'teleporting' and 'grabbing objects' in the VR environment.

EXPERIMENT RESULTS

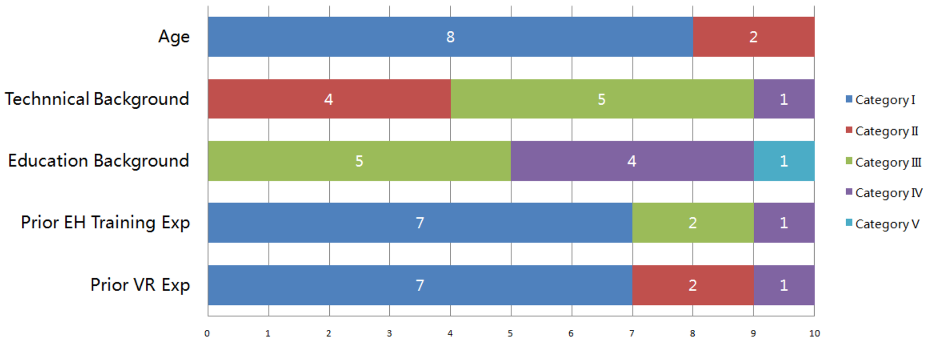

Figure 5. Sample distributions on five personal features

In our pilot study, we recruited ten participants. Each participant attended three sessions: the first two sessions are for the first scenario with 5-10 minutes' break in between and the third session is for the second scenario and is typically conducted a week later. Figure 5 gives the sample distributions in terms of five personal features: Age, Technical Background, Education Background, Prior EH Training Exp (Prior emergency health training experience) and Prior VR Exp (Prior VR experience). For each feature, we defined five different categories I-V (larger means higher). Each category has a predefined meaning, e.g., for Age, Category I refers to 18 - 29 years, and Category II refers to 30 - 39 years, etc. As we have a relatively small sample space, not all categories have a sample and this is reflected in the figure. We keep all the categories for the sake of completeness and future studies.

We now analyse the performance data collected on the thirty training sessions and its relation to the personal data. Two main performance measures we'll discuss below are timespan and moving distance. We first show how they are affected by repeated trainings, and then we show the relative impact of personal features on timespan. Finally we'll show the influence of language and handedness on the results.

Effect of Repeated Trainings

Our system collected the timespan for all subtasks in each session. Below we only use the full timespan, which is the sum of all subtasks' timespan. The average timespan over ten participants in the three training sessions are 1352.4 seconds, 737 seconds and 502.3 seconds respectively. This suggests that repeated trainings reduce the average timespan. We want to see if this also holds for each personal feature. Due to space limit, we only demonstrate evaluations on the first two personal features: Age and Technical Background. Further details can be found in (Peng 2018).

Timespan Evaluation on Age

Figure 6 shows the average timespan by different age categories among all training sessions. A decreasing trend can be observed on both age categories. In the first training session, the average timespan of Age Category I is 1268 seconds, which is 25.1% less than the Age Category II's 1692 seconds. Both categories' timespan difference in the second session is much less (Age Category I = 728 seconds, Age Category II = 775 seconds). In the third session, Age Category I spent 472 seconds on average, which is 24.3% less than that of Age Category II (623 seconds).

From the data, we may conclude that, with repeated trainings, participants in different age categories improved their performance with reduced average timespan. The younger age category spent less time than the older category, but the VR training is effective to close the gap.

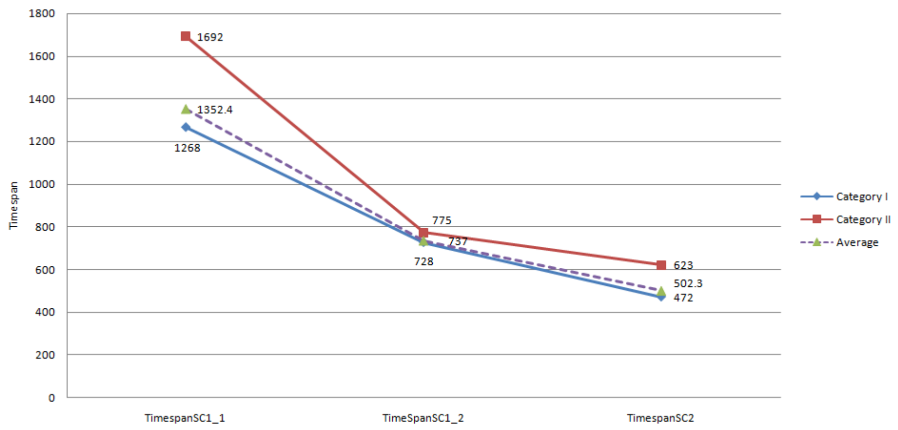

Figure 6. Average Timespan by Age among all sessions

Timespan Evaluation on Technical Background

Figure 7 shows the average timespan on Technical Background among all sessions. In the first session, a significant gap is shown between Category II and III (733 seconds), while the gap between Category III and IV is much smaller (68 seconds). In the second session, the gap between Category II and III is reduced to 18 seconds, and the Category II spent 59.1% less time than the first session. In the third session, the timespan among all categories are reduced as well. From the data, we may conclude that, with repeated trainings, participants in different technical background categories improved their performance with reduced average timespan. The participants in the stronger technical background category spent less time than the weaker ones, but the VR training is effective to close the gap.

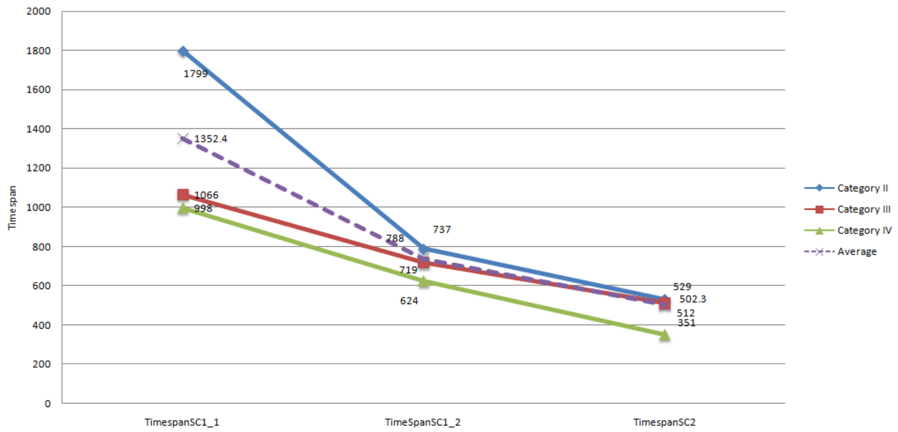

Figure 7. Average Timespan by Technical Background among all sessions

Moving Distance Evaluation on Technical Background

Besides the evaluation on the timespan, we evaluate moving distance of avatar and controllers. Due to space limit, we only show the result on Technical Background and refer more results to (Peng 2018).

Figure 8 shows the average moving distance of avatars by Technical Background among all sessions. Category IV increased the moving distance of their avatars during the second session, while the Category II and III kept a decreasing trend among all sessions. After reviewing the media stream data and talking with the only participant in Category IV, we found that the participant was trying to explore the virtual environment, instead of focusing on the tasks. This explains why Category IV increased the moving distance in the second session.

Figure 9 shows the average moving distances of left and right controllers by Technical Background among all sessions. Overall, decreasing trend of controller moving distance is observed for both left and right hands. Together with Figure 8, we can see that the increase and decrease trends of the controller moving distance have a correlation with that of the avatar moving distance for the same category, e.g., for Category IV, the right controller moving distance increases in the second session and the avatar moving distance increases too in the same session. The convergence of the moving distance both in the avatar and controllers for the second and third sessions in both category II and III shows the effectiveness of our training system.

From the data, we may conclude that, with repeated trainings, participants in different technical background categories improved their performance with reduced moving distance in general.

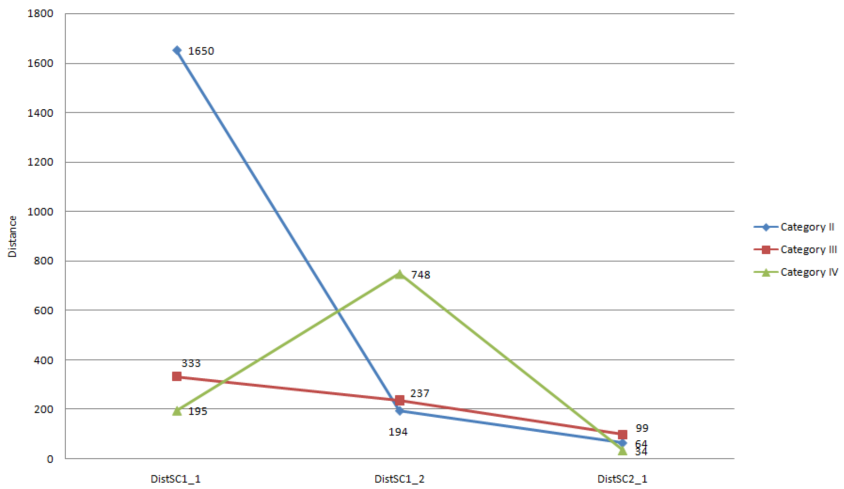

Figure 8. Average moving distance of Avatar by Technical Background among all sessions

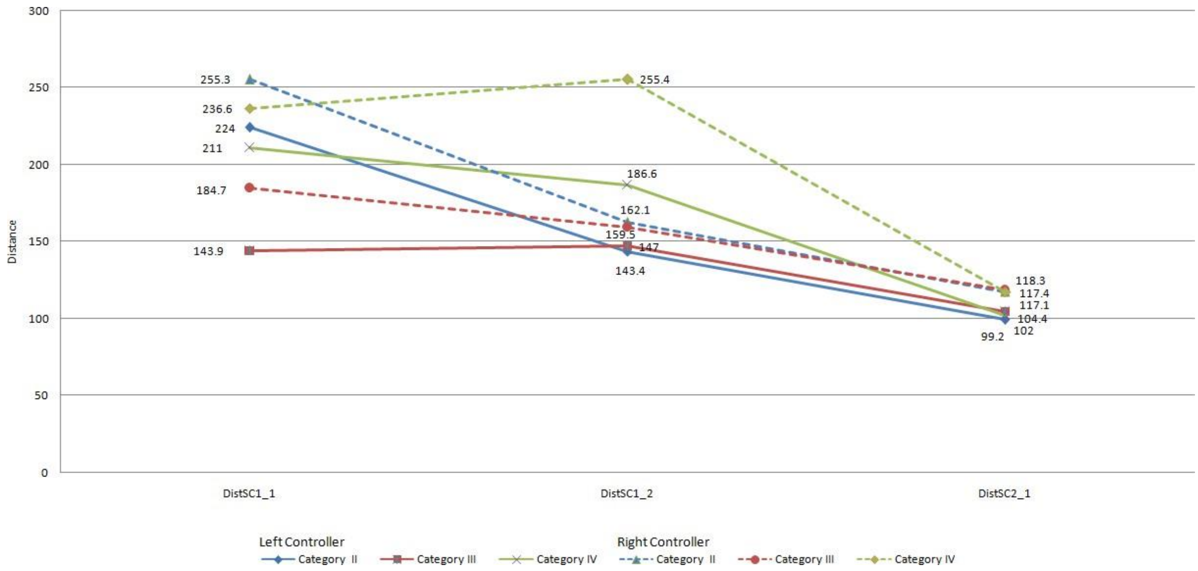

Figure 9. Average Moving Distance of Left and Right Controllers by Technical Background among all sessions

Relative Impact of Personal Features

Now we compare the relative impact of personal features on the timespan. For each session, we calculate the average of each categories (e.g., see Figure 6 and 7 for Age and Technical background in terms of timespan), and its distance to the overall average (i.e., on all participants). Suppose the overall average is v, and the average of each category is: s_1, s_2, ..., s_n, then **the relative deviation** for each training session t is given as

$$rd_t = \sqrt{\frac{\sum_{i=1}^{n}(\frac{s_i}{v} - 1)^2}{n}}$$

(1)

We use the relative deviation as an indicator for the impact of different personal features. In the following, we apply the relative deviation on timespan, but it can be applied on moving distance too.

For the Age feature, we use Formula (1) to calculate the relative deviations rd_t on the training sessions: rd_{t_1} = 0.18, rd_{t_2} = 0.03 and rd_{t_3} = 0.17. It shows that the first training session has the largest relative deviation, and then the gap is reduced notably in the second session. The smaller rd_t value means the categories' timespan is closer to the overall average timespan. In the third session, the relative deviation is increased again, possibly due to the change of scenario and the long recall time (one week).

All the relative deviations of five personal features are shown in Table 1. We can see that Technical Background at the first session has the highest relative deviation. This is consistent with our observation during the experiment that different technical background would strongly affect participants' performance in their first training session. The technical background affects the participants' understanding of the operations in the virtual world; and in general, the ones with higher technical background adapt to the virtual world quicker, hence spending less time. In the second session, the relative deviations for all personal features are reduced, see (rd_{t_1} - rd_{t_2}) in Table 1, as participants are getting familiar with the same training content. The relative deviation for Technical Background is reduced most. In the third session, the relative deviations increase again for all personal features, as participants are getting a new scenario and there is a longer time gap (1 week) with the second session. By comparing the first and last session, the relative deviations are mainly reduced and the most notable one is by Technical background, see (rd_{t_1} - rd_{t_3}) in Table 1. This suggests that the Technical Background has the highest impact on the timespan initially and it is reduced most significantly after repeated trainings. On the other hand, we see that the Prior VR Exp has the lowest relative deviation among all sessions. This suggest that the Prior VR Exp has the lowest impact on the timespan.

Influence of Language and Handedness

We found an interesting phenomenon according to the on-experiment observation, that the native English speakers preferred to use vocal instructions to acquire task information, while the non-native English speakers preferred to read the texts from the Task Helper. This phenomenon happened among all participants in their first training session. By listening to the vocal instructions and performing the tasks, the native English speakers spent 36% less time than the non-native English speakers in the first session. In the second session, the difference of timespan between two categories are reduced to 13.5%, as participants in both categories have partially memorised the training content and they did not fully rely on the instructions. In the third session, as small changes were made in a few subtasks, and the gap of timespan between two categories is increased to 29.5%.

Another interesting phenomenon is the handedness. We found that for each category, the average moving distance of the right controller is always larger than that of the left controller (see Figure 9 for the Technical Background feature), and their difference is more or less the same. We think that this is likely caused by the fact that most people are right-handed.

Table 1. The relative deviation on three sessions over personal features

	rd_{t_1}	rd_{t_2}	rd_{t_3}	$(rd_{t_1} - rd_{t_2})$	$(rd_{t_1} - rd_{t_3})$
Age	0.18	0.03	0.17	0.15	0.01
Technical Background	0.27	0.09	0.17	0.18	0.10
Education Background	0.17	0.08	0.18	0.09	-0.01
Prior EH Training Exp	0.22	0.13	0.26	0.09	-0.04
Prior VR Exp	0.16	0.01	0.13	0.15	0.03

CONCLUSION

In this research, we explore of the usage of Virtual Reality (VR) technology in an emergency healthcare training setting. We first constructed emergency healthcare workflows from reference sources, converted them into process diagrams, and developed a VR software that allows users to carry out the processes a virtual environment. We designed experiments collecting personal data and the performance data generated during the training sessions. Ten participants were recruited and each performs three training sessions. We evaluate the data collected and have the following two main conclusions based on the performance of ten participants: (a) despite the different personal features, the participants, after repeated trainings, can improve their performance with reduced timespan and moving distance; and (b) the Technical Background has the highest impact on the timespan initially and it is reduced most significantly after repeated trainings; meanwhile, the Prior VR Exp has the lowest impact on the timespan. We also notice the influence of language on time span and the influence of handedness on moving distance. Note that as the sample space is relatively small, our conclusions are limited in generality, and a larger sample collection would be preferred. Finally, we point out some directions for future work: (1) further analysis on current data collection using more complex algorithms; (2) conduct further experiments for a lager sample collection; (3) an integration of this VR software in training emergency responders with organisations such as St John.

REFERENCES

Aggarwal, R., Grantcharov, T. P., Eriksen, J. R., Blirup, D., Kristiansen, V. B., Funch-Jensen, P., and Darzi, A. (2006) An evidence-based virtual reality training program for novice laparoscopic surgeons, *Annals of surgery* 244.2, pp. 310–314.

Amiel, J. (2015) The Switch from Unity 3D to Unreal Engine, retrived from http://www.extroforge.com/the-switch-from-unity-3d-to-unreal-engine/.

Bhide, S., Riad, R., Rabelo, L., Pastrana, J., and Katsarsky Alexander & Ford, C. (2015) Development of Virtual Reality Environment for Safety Training, *IIE Annual Conference.Proceedings*, pp. 2302–2312.

Burke, M. J., Sarpy, S. A., Smith-Crowe, K., Chan-Serafin, S., and Salvador Rommel O. & Islam, G. (2006) Relative effectiveness of worker safety and health training methods, *American journal of public health* 96.2, pp. 315–324.

Costa, C. and Stelescu, I. õ. (2014) Increasing the efficiency of the training programs for the mine rescue teams, *Annals of the University of Petroşani*, *Economics* 14.Part 1.

CRED (2016) Disaster Trends, Available from http://www.emdat.be/disastertrends/index.html. Given, L. M.

(2008) *The Sage encyclopedia of qualitative research methods*. Sage Publications.

Hilton, D., Cobb, S., Pridmore, T., and Gladman John & Edmans, J. (2011) Development and evaluation of a mixed reality system for stroke rehabilitation, *Advanced Computational Intelligence Paradigms in Healthcare 6. Virtual Reality in Psychotherapy, Rehabilitation, and Assessment*, pp. 193–228.

Izard Santiago González, M . n. J. A. J. (2016) Virtual Reality Medical Training System, *Proceedings of the Fourth International Conference on Technological Ecosystems for Enhancing Multiculturality*. New York, NY, USA: ACM, pp. 479–485.

Khnapfel, U. et al. (2000) Animation and simulation techniques for vr-training systems in endoscopic surgery, *Computer Animation and Simulation 2000*. Springer, pp. 173–185.

Kilmon, C. A., Brown, L., and Ghosh Sumit & Mikitiuk, A. (2010) Immersive Virtual Reality Simulations in Nursing Education, *Nursing Education Perspectives* 31.5, pp. 314–7.

Larsen, C. R., Soerensen, J. L., Grantcharov, T. P., Dalsgaard, T., Schouenborg, L., Ottosen, C., and Schroeder Torben V. & Ottesen, B. S. (2009) Effect of virtual reality training on laparoscopic surgery: randomised controlled trial, *Bmj* 338, b1802.

National Institute for Occupational Safety and Health Office for Mine Safety and Health Research Pittsburgh Research Laboratory (2000) Mine Emergency Response Interactive Training Simulation (MERITS).

Rizzo, A., Pair, J., Graap, K., Manson, B., McNerney, P. J., Wiederhold, B., and Wiederhold Mark & Spira, J. (2006) A virtual reality exposure therapy application for Iraq War military personnel with post traumatic stress disorder: From training to toy to treatment, *NATO Security through Science Series E Human and Societal Dynamics* 6, p. 235.

Schofield Damian & Dasys, P. G. C. A. P. A. (2009) The use of virtual simulators for emergency response training in the mining industry, *Journal of Emergency Management* 7.6, p. 1.

Soderholm, H. M., Sonnenwald, D. H., Manning, J. E., Cairns, B., and Welch Greg & Fuchs, H. (2008) Eploring the potential of video technologies for collaboration in emergency medical care: Part II. Task performance, *Journal of the American Society for Information Science & Technology* 59.14, pp. 2335–2349.

St John (2013) Clinical Procedures and Guidelines Comprehensive Edition 2013-2015.

St John (2018) How to assess a casualty. Ed. by St John. url: http://www.sja.org.uk/sja/first-aid- advice/what-to-do-as-a-first-aider/how-to-assess-a-casualty.aspx.

Yamato, T. P., Pompeu, J. E., and Pompeu Sandra M. A. A. & Hassett, L. (2016) Virtual Reality for Stroke Rehabilitation, *Physical Therapy* 96.10, pp. 1508–151.

Xia P. (2018) Enhanced healthcare with virtual reality, Master of Philosophy Thesis, Auckland University of Technology, retrieved from http://hdl.handle.net/10292/1178