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Navigation Hints in Serious Games

Vidya Bommanapally(✉), Mahadevan Subramaniam, Parvathi Chundi, and Abhishek Parakh

College of Information Science and Technology, University of Nebraska-Omaha, Omaha, USA.
{vbommanapally, msubramaniam, pchundi, aparakh}@unomaha.edu

Abstract. Serious games provide an engaging environment for students to learn complex concepts. A novel approach for players to achieve learning objectives in a serious game while avoiding potential distractions due to game elements is described. The proposed approach observes player performance in the game exercises and automatically suggests other unexplored exercises to the player. The exercises suggested are selected using a numeric value which is computed based on the uniqueness and the freshness of the concepts underlying the exercises. The approach was implemented in a quantum computing game, *QuaSim*. Our experiments involving 81 players show that the proposed approach aids players to learn quantum computing concepts in an engaged manner.

Keywords: Serious Games · Learning.

1 Introduction

Serious games are a promising approach to meet the learning objectives while providing an engaging learning experience to the players of these games. Serious games have achieved impressive successes in learning in diverse fields including the physical and mathematical sciences, linguistics, game theory and problem solving [1–4]. However, designing serious games that meaningfully combine learning along with engagement continues to be a challenging problem. Games emphasizing education often tend to be media-rich concept practice sessions where game scenarios are repeated until a certain player performance level is attained[5, 6]. Alternatively, certain games tend to over-emphasize the gaming elements to the point where they tend to distract players from achieving the desired educational objectives [7–9].

In this paper, we describe a novel approach that combines the achievement of learning objectives and player engagement while avoiding distractions. In the proposed approach, players must become proficient in a set of knowledge concepts to achieve the learning objectives. Each exercise in the game is tagged with a set of knowledge concepts that the player will become proficient in upon solving that exercise. Player performance in the game exercises is continually observed by the game and used to automatically navigate players to other unexplored exercises. A numeric value is assigned to each exercise based on two

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aspects – degree of uniqueness of an exercise in covering a knowledge concept among all exercises covering that concept and the degree of freshness of exercise in exposing a relatively unexplored concept to a player. In each game scenario, upon completion of an exercise, the values of the remaining exercises are automatically determined and players are navigated to exercises with a high value.

The proposed approach has been implemented in a serious multi-player game, *QuaSim*, that provides a hands-on immersive experience to students and professionals to explore quantum computing, algorithms and cybersecurity protocols. The *QuaSim* scenarios comprise of several exercises such as programming quantum machinery to activate certain energy receptors at different locations in a city in order to learn quantum computing basics. The *QuaSim* scenarios also include multi-player exercises with players communicating secrets over quantum channels while others try to eavesdrop or teams of players launching cyber-attacks on some city infrastructure using quantum devices while others defend. *QuaSim* incorporates the proposed approach as an automatic navigation hint generation procedure, *nhint*, which in each scenario suggests the next game exercise to a player. The *nhint* procedure is available in *QuaSim* in two modes – automatic mode (*a-hint*) where a player is automatically teleported to the next exercise and semi-automatic mode (*sa-hint*) where a player may ignore the suggested exercise.

Our experiments studied the effectiveness of the *nhint* procedure with 81 players. The *QuaSim* game with three modes of *nhint* procedure *nohint* (disabled *nhint*), *a-hint*, and *sa-hint* were played by roughly equal sized groups of players and the effectiveness of *nhint* modes were measured as a ratio of the proficiency achieved to player engagement. The latter was measured in terms of player persistence based on the number of exercises solved. We also studied how many exercises the players using the *a-hint* mode were able to solve correctly in the first attempt in comparison to those using the *nohint* mode. We also conducted a qualitative survey about the player experience with the *QuaSim* in the three modes. Our results show that player proficiency to persistence ratio were highest for the *a-hint*, followed by *sa-hint*, with *nohint* being the least. The *QuaSim* game with *a-hint* also exhibits a superior correct in the first attempt performance. However, in the post-game qualitative surveys, the *QuaSim* with the *sa-hint* was ranked the highest for engaging experience by the players.

1.1 Related Work

Recently, the incorporation and generation hints in serious games has gained considerable interest [1, 6, 10, 11]. Hints in these games trace their origins to the study of hints in intelligent tutoring systems (ITS) where hints guide students to produce the correct solution to a given problem. Previous student data about correct solutions are often used to generate hints that aid a student to complete their partial solution attempts [6]. Inspired by hint generation in ITS's, Conati et al [1] incorporated hints into the game Prime Climb and showed that hints improve mathematical learning in the game. They also studied how drawing a player attention to hints affects learning as well as player perception of

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the utility of hints. In [11], O'Rourke et al incorporated abstract and concrete hints into the math game Refraction. Their work was solely focused on studying the effect of these hints on player performance in math learning. In [6], Wauck and Fu proposed hints targeted at improving engagement in a simple board game. They associate player engagement to the new squares visited by players in a period time and generate hints that highlight unexplored squares. The proposed approach significantly differs from these works in designing hints to simultaneously improve player learning and engagement. In order to achieve this, a numeric value is assigned to each exercise that combines both the learning and engagement dimensions. The knowledge components associated with the exercise are used to assess the *learning potential* of an exercise. Exercises that cover unique knowledge components contribute highly learning component of the value metric. The *engagement potential* value of an exercise is determined based on the player history. Exercises with knowledge components that a player has not encountered earlier or exercises that present previously seen knowledge components in a different context are rated highly on the engagement potential. On the other hand, exercises involving knowledge components that players have encountered earlier exercises and successfully solved are rated low for the engament potential.

2 A Quantum Serious Game

The *QuaSim* is a 3-D interactive game built using the Unreal Engine 3D platform extended to embed instructional videos, web browsers, audio dialogues, auto-graded quizzes, and tests. The *QuaSim* game scenarios are played at different locations of a city including high-rise buildings as well as open spaces. The *QuaSim* includes four single-player scenarios about quantum computing basics and two multi-player scenarios about quantum communication protocols and security attack and defense exercises. In this paper, we focus on the single-player scenario introducing the concept of mapping qubits (quantum bits) onto polarized photons, which we refer to as *qubit game scenario*. Details regarding other *QuaSim* game scenarios will be discussed in an expanded version of this paper.

In the qubit game scenario, several qubit receptors located at different levels of a building must be activated by programming qubits with proper orientation using a given representation of photon. A receptor specifies an angle and accepts qubits programmed at an angle that is either the same, orthogonal to, or in the opposite quadrant to the specified angle. These different types of programming of the qubits make up different exercises. In addition, the programming of the qubits in each exercise must be performed using either the matrix, ket or linear combination of vector representations of the photons. For example, the Figure 1(a) depicts a receptor that is activated by programming a qubit at an angle that is in the opposite quadrant using the matrix notation. The specified angle of 255 degrees is embedded in the green photons in the Figure 1(a) and the player workspace on the left depicts the matrix values used to produce this orientation.

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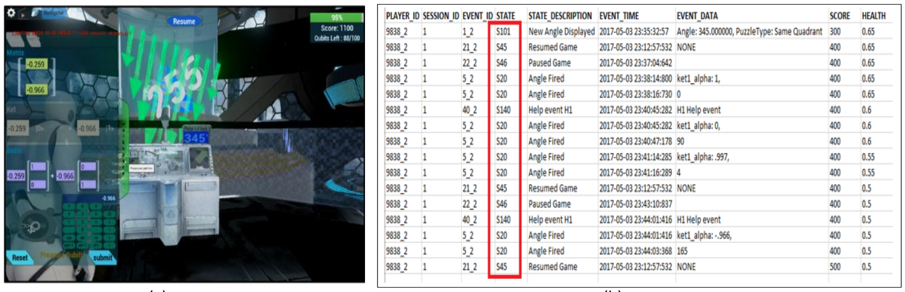

PLAYER_ID	SESSION_ID	EVENT_ID	STATE	STATE_DESCRIPTION	EVENT_TIME	EVENT_DATA	SCORE	HEALTH
9838_2	1	1_2	S101	New Angle Displayed	2017-05-03 23:35:32:57	Angle: 345.000000, PuzzleType: Same Quadrant	300	0.65
9838_2	1	21_2	S45	Resumed Game	2017-05-03 23:12:57:532	NONE	400	0.65
9838_2	1	22_2	S46	Paused Game	2017-05-03 23:37:04:642		400	0.65
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:38:14:800	ket1_alpha: 1,	400	0.65
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:38:16:730	0	400	0.65
9838_2	1	40_2	S140	Help event H1	2017-05-03 23:40:45:282	H1 Help event	400	0.6
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:40:45:282	ket1_alpha: 0,	400	0.6
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:40:47:178	90	400	0.6
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:41:14:285	ket1_alpha: .997,	400	0.55
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:41:16:289	4	400	0.55
9838_2	1	21_2	S45	Resumed Game	2017-05-03 23:12:57:532	NONE	400	0.5
9838_2	1	22_2	S46	Paused Game	2017-05-03 23:43:10:837		400	0.5
9838_2	1	40_2	S140	Help event H1	2017-05-03 23:44:01:416	H1 Help event	400	0.5
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:44:01:416	ket1_alpha: -.966,	400	0.5
9838_2	1	5_2	S20	Angle Fired	2017-05-03 23:44:03:368	165	400	0.5
9838_2	1	21_2	S45	Resumed Game	2017-05-03 23:12:57:532	NONE	500	0.5

(a) (b)

Fig. 1: a) Opposite quadrant, matrix exercise, (b) Sample player action data log.

The player performance is depicted on the upper right by the score and the number of available qubits.

The qubit game scenario has a total of 12 exercises involving a combination of two knowledge concepts – the qubit orientation (3 possible values) and its representation (3 possible notations). Out of these, 9 exercises are basic and 3 are derived by composing the concepts. Each basic exercise is designed to achieve proficiency across the pair of values of orientation and notation concepts whereas the derived exercises require programming the qubit at a particular orientation using multiple representations. These derived exercises serve like a comprehensive test over the concepts learned through the basic exercises. The same format is used across all the *QuaSim* scenarios.

3 Navigation Hints

In general, any *QuaSim* scenario, $G = \{e_1, \ldots, e_n\}$ is a set of n-exercises over a set of concepts $C = \{c_1, \ldots, c_k\}$. The tuple of concepts relevant to an exercise e_i in G is $R(e_i)$. Two distinct exercises e_i and e_j in G are said to be *related* if they share one or more relevant concepts. The set of exercises covering a concept c_j, $E(c_j)$, consists of all the exercises where c_j is relevant. The *concept proficiency* is measured based on exercises covering a concept. The concept proficiency for a concept c_j has the value 1 if the player has solved some exercise in $E(c_j)$ and has the value 0 otherwise. We will assume that there is no dependency among concepts in terms of their proficiency, i.e., achieving proficiency in one or more concepts is not a pre-requisite to achieve proficiency in any of the other concepts. The *scenario proficiency*, $P(G)$ for scenario G, is a k-tuple of Boolean values whose j^{th} component has value 1 if the player is proficient in concept c_j and has value 0 otherwise. Initially, all the components $P(G)$ have the value 0. Scenario proficiency $P(G)$ is *complete* if all of its components have the value 1.

In a *QuaSim* scenario, a player can choose the exercises they want to play. But this some times may lead to situations where a player may take too long to achieve scenario proficiency and may lose interest in the game. We describe a automatic hint generation procedure, *nhint* towards addressing problem. The

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nhint procedure records the player performance (correct or incorrect) at each exercise in a given scenario and determines a set of exercises that the player can attempt next. These are determined by the *nhint* procedure by associating a value with each of the exercises that can be attempted next by a player. The value of an exercise e_i, $v_i = \langle \frac{1}{|E_r(c_j)|},\ c_j \in R(e_i)\rangle$. So, each value v_i is k-tuple whose j^{th} component denotes the number of exercises where the concept c_j is relevant. The j^{th} component of v_i is 0 then the concept c_j is not relevant to exercise e_i. If j^{th} component of v_i is 1 then the concept c_j is relevant only to exercise e_i, meaning that e_i is essential to achieve proficiency in concept c_j.

The *nhint* is an iterative procedure, where in each iteration an exercise with the maximum value among the available exercises is a candidate for the player to attempt next. Ties if any, among the candidate exercises are broken arbitrarily. If the player solves a candidate exercise e_i, the components of $P(G)$ corresponding to the concepts in $R(e_i)$ are set to value 1. The coverage of all concepts belonging to $R(e_i)$ is set to 0 in every remaining related exercise since the player has achieved proficiency in these concepts by solving e_i. Then, the exercise e_i is removed, the value of the remaining exercises are recomputed using the updated coverage values, and the exercise with the highest value is chosen for the next iteration. On the other hand, if the player fails to solve exercise e_i, $P(G)$ is unchanged. The coverage of concepts are unchanged as well since failure does not modify the proficiency in any of the concepts. The exercise e_i is removed, the values of the remaining exercises is recomputed, and the exercise with the highest value is chosen for the next iteration. The procedure terminates with *success* if all components of $P(G)$ are set to 1 and it terminates with *failure* if there are insufficient exercises to achieve proficiency in the rest of the concepts.

Example: Consider the qubit game scenario $G = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, e_9\}$ with 9 basic exercises over the set of concepts $C = \{$*M(matrix)*, *K(Ket)*, *L(Linear-combination)*, *S(Same-angle)*, *R(Orthogonal)*, *P(Opposite-angle)*$\}$. The set of relevant concepts to the individual exercises are: $R(e_1)=\langle M, S\rangle$, $R(e_2)=\langle M, R\rangle$, $R(e_3)=\langle M, P\rangle$, $R(e_4)=\langle K, S\rangle$, $R(e_5)= \langle K, R\rangle$, $R(e_6)=\langle K, P\rangle$, $R(e_7)=\langle L, S\rangle$, $R(e_8)=\langle L, R\rangle$, $R(e_9)=\langle L, P\rangle$. The scenario proficiency vector for G, $P(G) = \langle M,S,K,R,L,P\rangle$. A play session guided by the *nhint* procedure where all exercises suggested by *nhint* procedure are solved correctly by a player is indicated in Table 1. The *nhint* procedure ends with success in this session. The *nhint* terminates with success since the player achieves proficiency in all of the concepts in the scenario[1]. The rows 1-4 in the 1 depict the different exercises attempted by the player as suggested by *nhint* and the effects of the player attempts on the scenario proficiency and the next exercise suggested by *nhint*. Each of the nine exercises $e_1 \ldots e_9$ have two relevant concepts each and each of these concepts is shared among exactly three exercises, the values $v_1 = \ldots = v_9 = \langle \frac{1}{3}, \frac{1}{3}\rangle^2$ of all the available exercises are the same. Initially, the exercise e_1 is randomly selected by *nhint* and is solved successfully by the player. As a result, first, the

[1] The components in steps are indicated only if they change. Further, the proficiency values of the remaining exercises are only shown.

[2] For brevity, we indicate only the non-zero components in the value 6-tuple.

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Table 1: Quantum Basics Session Guided *nhint* with no failed attempts.

1. (e_1, $v_1 = \ldots = v_9 = \langle \frac{1}{3}\ \frac{1}{3} \rangle$,	$P(G) = \langle 000000 \rangle$)
2. (e_5, $v_2 = v_3 = \langle 0, \frac{1}{3} \rangle$, $v_4 = v_7 = \langle \frac{1}{3}, 0 \rangle$,	$P(G) = \langle 110000 \rangle$)
3. (e_9, $v_2 = v_4 = \langle 0,0 \rangle$, $v_6 = \langle 0, \frac{1}{3} \rangle$, $v_8 = \langle \frac{1}{3}, 0 \rangle$,	$P(G) = \langle 111100 \rangle$)
4. (S, $v_1 =, \ldots, = v_9 = \langle 0,0 \rangle$	$P(G) = \langle 111111 \rangle$)

exercise e_1 is removed from the set of available exercises. Then, the values of the related exercises v_2 and v_3 are updated by setting their first component to 0 to mark proficiency in the matrix notation concept(M). Similarly, the values of the related exercises v_4 and v_7 are updated to indicate proficiency in the same angle qubit orientation concept (S). The values of the remaining exercises are (unchanged values are not indicated in the table above) higher than the exercises v_2, v_3, v_4, and v_7 and hence any of them can be suggested by *nhint* to the player to attempt next. Exercise e_5 is chosen randomly and solved correctly. As a result, the exercise e_5 is removed and the values of the related exercises are updated as shown above. Finally, the exercises e_9 is chosen for the player to attempt since it has the maximum value. The player achieves proficiency in two concepts by solving each of the exercises and the corresponding elements in $P(G)$ are set to value 1 after each correct attempt. The player achieves proficiency in all the concepts in the scenario upon solving the three exercises and hence *nhint* terminates with success (shown by S in row 4 above).

4 Experimental Results

Three versions of the *QuaSim* game suppporting the three *nhint* modes (*nohint*, *a-hint*, and *sa-hint*) were played by 81 players that included 20 females and 61 males, 68 graduate students, 2 seniors and 1 freshman and 10 cybersecurity professionals. The *QuaSim* was played in a media lab on individual desktops with Intel i7 @ 3.40 GHz processor, 16GB RAM running Windows 10 Enterprise 2016. The NVIDIA GeForce GT 730 graphic card was available on each machine to support the Unreal graphics. After an IRB consent for data collection, players register with a given anonymous id and email address and login to play the game scenarios for about an hour. The *QuaSim* assigns each player a unique player id and logs every action of the players in the *QuaSim* database (SQLite3). See 1(b) for a sample of the collected data. Students were also given a post-game qualitative survey regarding their engagement levels, and hints. The main objective of our experiments was to study player proficiency and engagement in scenarios and whether these two aspects can be improved by using the *nhint* procedure. Player proficiency ratio, $Pr = \frac{pc}{|C|}$ where pc is the number of concepts where a player is proficient and C is the total number of concepts in a scenario was used to track proficiency. Player engagement was measured qualitatively through post-game surveys as well as quantitatively using the number of exercises attempted and the play time. The proficiency to effort for a scenario, $PE = \frac{Pr}{|E_s|}$ was used to measure the proficiency attained by a player with respect to the

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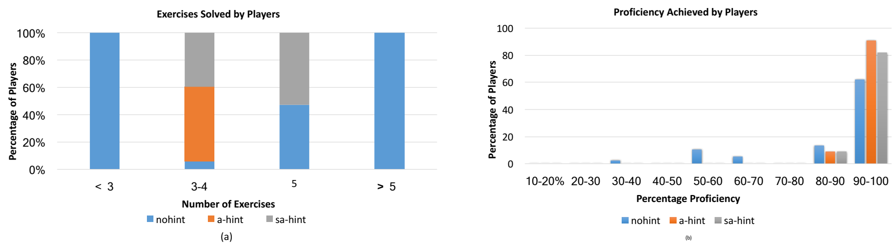

Fig. 2: Proficiency and Engagement: a) Percentage of exercises solved, b) Percentage Proficiency achieved.

number of exercises that they solved (E_s). Our results regarding the number of exercises solved by players, the proficiency achieved by them in the qubit scenario, as well as the proficiency to effort ratio across the three versions of the game are depicted in Figure 2. The X-axis in Figure 2(a) is the number of exercises solved by the players and the Y-axis is the percentage of players that solved those many exercises. We grouped the number of exercises solved into 4 buckets to highlight the difference across the three modes. As evident from this figure, *a-hint* version players solved 3-4 exercises. The *sa-hint* version players solved 3-5 exercises whereas only the *nohint* players greater than 5 exercises. Thus, we can conclude that in general, the effort of *nohint* version players was greater than the *sa-hint* players which was almost the same as that of *a-hint* players. Further, only the *nohint* players solved less than 3 exercises indicating that this version was not engaging enough for them to persist. Figure 2(b) depicts the proficiency ratio Pr (as a percentage) achieved by players. The X-axis is the Pr percentage and the Y-axis is the percentage of players. It is clear from this figure that all *a-hint* version players achieved over 80% proficiency (in fact over 90% of these players achieved 90-100% proficiency) whereas around 90% of the *sa-hint* players were able to achieve such proficiency. On the other hand, the proficiency achieved by the *nohint* players peaked around 60% that was well below those of the other two groups. The left side of Figure 3 depicts the PE results for these three groups. The X-axis the PE percentage and the Y-axis is the percentage of players. It is clear from this figure that the proficiency to effort ratio for *a-hint* is the highest followed by that of the *sa-hint* players, and both these player groups performed much better than the *nohint* version players. From this figure, we conclude that the *a-hint* and *sa-hint* versions are promising in helping players achieve scenario proficiency while maintaining engagement measured in terms of the player effort.

The *nhint* procedure is designed to choose exercises based on their concept freshness *i.e.*, concepts that players have not encountered in earlier exercises. We studied the effect of such a choice on players solving a problem on their very first attempt. The results are depicted in the right side of Figure 3. The X-axis consists of the 12 exercises in the qubit game scenario and the Y-axis is the percentage of players who solved the exercises correctly in their first attempt. It

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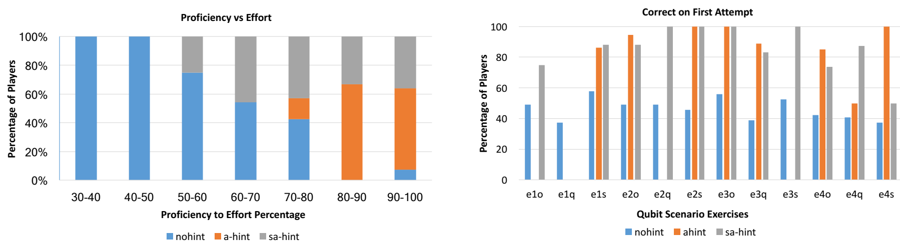

Fig. 3: Correct on First Attempt with and without hints

is easy to see that players using the *a-hint* versions outperformed those playing the *nohint* version by a wide margin in all the exercises that they played. Note that some of the exercises such as e10, e1q, e21 and e3s have zero *a-hint* players since the *nhint* procedure did not assign them these problems. This is because the relevant concepts in these exercises were already covered elsewhere. The result for *sa-hint* version players are very similar to those for the *a-hint* players.

5 Conclusion

We have described a novel approach for players to achieve the learning objectives in an engaging gaming environment while avoiding potential distractions due to game elements. The proposed approach observes player performance in the game exercises and automatically suggests other unexplored exercises to the player. The exercises suggested are selected using a value which is computed based on the uniqueness and the freshness of the concepts underlying the exercises. The approach was incorporated into a quantum cryptography game, *QuaSim* and was played by 81 graduate students and cybersecurity professionals. Our results show that the proficiency achieved by the players can be improved by the use of these hints while retaining their engagement measured in terms of their persistence in the game. While user choice of acting on hints (*sa-hint*) was preferred over fully automated hints (*a-hint*) by players in the post-game survey, both these forms of hints enabled players to solve many more problems correctly in their very first attempt when compared to the version where no hints were available.

6 Acknowledgement

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