Interactive Ant Colony Optimization to Support Adaptation in Serious Games

Michael D. Kickmeier-Rust[1], Andreas Holzinger[2]
[1] *St. Gallen University of Teacher Education, Switzerland*
michael.kickmeier@phsg.ch
2 Institute for Medical Informatics, Statistics & Documentation,
Medical University Graz, Austria
andreas.holzinger@medunigraz.at

Abstract

The success of serious games usually depends on their capabilities to engage learners and to provide them with personalized gaming and learning experiences. Therefore, it is important to equip a game, as an autonomous computer system, with a certain level of understanding about individual learning trajectories and gaming processes. AI and machine learning technologies increasingly enter the field; these technologies often fail, however, since serious games either pose highly complex problems (combining gaming and learning process) or do not provide the extensive data bases that would be required. An interesting new direction is augmenting the strength of AI technologies with human intuition and human cognition. In the present paper, we investigated performance of the MAXMIN Ant System, a combinatorial optimization algorithm, with and without human interventions to the algorithmic procedure. As a testbed, we used a clone of the Travelling Salesman problem, the Travelling Snakesman game. We found some evidence that human interventions result in superior performance than the algorithm alone. The results are discussed regarding the applicability of this pathfinding algorithm in adaptive games, exemplified by Micro Learning Space adaptation systems.

Keywords: *Game AI, Ant Colony Systems, Human in the Loop; Micro Learning Spaces*

1 Introduction

Serious games have arrived in mainstream educational settings at all level (school education, higher education, and even workplace learning). Serious games capitalize on their core strengths - distilled to its essence: fun, fantasy, curiosity, challenge, and control. These strengths lead to an enormous intrinsic motivational potential so that digital games can reach a broad audience. Also as a means of research, games have particular advantages. Many large machine learning/AI companies, for example, are designing experiments based on games, as highlighted by Bowers et al. [1]. A meta-review of Pieter Wouters and colleagues [2] revealed evidences about the effects of game-based learning along all dimensions, that is, primary (the intended learning outcome), secondary (side effects such as the improvement of attitudes), and tertiary (unpredictable positive and negative side effects). A recent meta-review by Clark and colleagues [3] yielded that digital games significantly enhanced student learning relative to non-game conditions.

In every digital game, players both act in and interact with the game. Players use the options of diverse game mechanics to achieve certain goals. The quality and the results of interactions determine the performance, which makes it a complex construct, subsuming the learning dimension, the emotional-motivational dimension, as well as the gaming dimension, as pointed out by Wiemeyer, Kickmeier-Rust, and Steiner [4]. Moreover, it includes processes of learning, teaching/instruction, and assessment, which in turn have complex mutual dependencies and are confounded with random game processes. Shute and Ventura [5] argue that many of the current assessment methods in tutorial systems are often too simplified, abstract, and decontextualized to suit educational needs. Assessment, specifically when it is supposed to be formative in nature, cannot be 'divorced' from learning processes. This, unfortunately, is the case in many everyday educational situations such as general exams and tests. An ideal formative assessment is not directly visible to learners but embedded into the entire learning process, with the aim of promoting real-time / just-in-time instruction. Shute, Hansen, and Almond [6] could demonstrate that such ideas of formative assessment, transferred to tutorial systems, significantly improve learning performance. The challenges for embedding the assessment procedures seamlessly in a game and of providing non-invasive adaptations are substantial. Consequently, the approaches to in-game assessment, stealth assessment, and non-invasive adaptation of games have been refined significantly over the past decade (cf. Bellotti and colleagues, [7]). State-of-the-art methods include the concept of stealth assessment as described by Shute [8], which is a method for embedding assessment seamlessly into games based on evidence-centered design. In addition, there exist structural, combinatorial models [9], cognitive classification models [10], Bayesian approaches [11], latent variable models [12] and also methods from the field of learning analytics research [13] and machine learning [14]. In this spirit, assessment must be based on simple identifiable indicators and it must be based on valid heuristics. According to Kickmeier-Rust and Albert [15], these indicators, thereby, may be divided into performance related aspects, emotional-motivational as well as personality related aspects. The performance related aspects include measuring, gathering, analyzing, and interpreting scores, task completion rates, completion times, success rates , success depths (the quality or degree to which a task has been accomplished), etc. The approaches to in-game assessment, stealth assessment, and non-invasive adaptation of games have been refined significantly over the past decade, as highlighted by Bellotti and colleagues [7]. State-of-the-art methods include the concept of stealth assessment by Shute [5], which is a method based on evidence-centered design, for embedding assessment seamlessly into games. There exist structural models, cognitive diagnostic models, Bayesian and latent variable models and also methods from the field of learning analytics. In addition to the psychometric approaches, more and more commercial game technologies and AI techniques from intelligent tutoring systems (cf. D'Mello and Greasser, [16]) and intelligent narrative technologies entered the genre (cf. Si, Marsella, and Pynadath, [17]). The solutions range from real-time narrative planning and goal recognition to affective computing models for recognizing student emotional states.

1.1 Game AI and Serious Game AI

The development of intelligent features for the improvement of gaming experiences has a long tradition in the context of entertainment games (cf. http://gameai.com). These techniques are manifold, their main goal is, however, making non-player characters (NPC) more credible and more serious opponents. In an overview article, James Lester and colleagues [18] mention following functions: (i) pathfinding algorithms for NPCs, (ii) Bayesian approaches for NPCs' decision making, and (iii) genetic algorithms to equip NPCs with learning mechanics. Pathfinding, for example, is a technique to determine how a non-player character (NPC) moves from one place to another, accounting for opponents, obstacles, and certain objectives.

Over the past years, sophisticated methods have been developed to increase the fidelity and credibility of computer game environments. An important inspiration is the improvement of combat simulations. However, with the increasing importance of serious games, the techniques of game AI seeped into this genre as well. More importantly, in the context of serious games, game AI approaches merged with the traditional approaches to educational AI (from the communities of adaptive and intelligent tutorial systems as well as open learning modeling) and established a completely new field, the serious game AI research.

The increasingly important role of AI in serious games is reflected by AI being the main theme of this years' Serious Games Conference in the context of the famous *CeBIT* fair. Leading experts discussed the role of current and future AI technologies in serious games. An anchor point in the discussions was *Google*'s *AlphaGo*, beating the world's best human player in the game *Go* (Silver et al., [19]). Serious games present a fusion of smart technologies and applications of computer game mechanics in "serious" areas on the other side and therefore can provide learners with innovative functionalities, features and advances. As Shute, Rieber, and Van Eck [20] pointed out, it is critical that intelligent (or smart, adaptive) educational systems and in particular serious games rely on important underlying pedagogical principles. These authors list four such principles: (1) employing sound game theory, (2) focusing on problem-based learning, (3) including situated cognition, and (4) including cognitive disequilibrium and scaffolding. Lester et al. [18] emphasize the utility of intelligent narratives in serious games and conclude: "because of their ability to dynamically tailor narrative-centered problem-solving scenarios to customize advice to students, and to provide real-time assessment, intelligent game-based learning environments offer significant potential for learning both in and out-side of the classroom" (p.43).

In a comprehensive review of the literature, based on 129 papers, regarding AI functions of serious games, Frutos-Pascual and Zapirain [21] summarize decision making functions, algorithms and techniques that are used for logical and rational decision-making processes on the basis of the available information about learners, and machine learning approaches. The former are subdivided into decision tree approaches, fuzzy logic techniques (specifically related to the control of NPCs), Markov systems, goal-oriented behaviors for NPCs, rule-based systems, and finite state systems.

A second aspect, highlighted by Frutos-Pascual and Zapirain, is machine learning. Ciolacu, Tehrani, and Beer [22] argue that machine learning in education will be the fourth revolution towards utilizing student data for improving learning quality and for accurately predicting academic achievements. Techniques for machine learning in serious games include Bayesian models, neural net-works, case-based reasoning, support vector machines, and cluster analyses. A prominent example is the research in the context of *Crystal Island* (http://projects.intellimedia.ncsu.edu/crystalisland/), which investigates the application of machine learning for performance assessment and adaptation in serious games [14].

In a recent article, Cristina Conati and colleagues [23] added an important aspect to the conversation about AI in education, that is, transparency and an opening of underlying reasoning processes of AI functions. The community of open learner modelling (OLM) is attempting to enable learners and other stakeholders to look be-hind the processes of intelligent functions and perhaps even disagree with the conclusions (this is researched by the community of negotiable/persuadable open learner models). Conati [23] argues that approaches for an interpretable and perhaps credible AI are necessary to increase the impact on learning. This claim is in center of this paper, although from a different angle. We argue that it is not only necessary to open the reasoning processes and make them interpretable, it may be desirable also, that humans can directly and intentionally influence algorithms, in order to improve their efficiency.

1.2 Human vs Computer

Machine learning algorithms became nearly omnipresent in today's online world. The basic idea is to develop techniques that reason over the existing vast amount of digital data and to "learn" from these data. An example, given by LeCun, Bengio, and Hinton [24], is the breakthrough achieved with deep learning on the task of phonetic classification for automatic speech recognition. Actually, speech recognition was the first commercially successful application of deep convolutional neural networks. Astonishingly, autonomous software is able to lead conversations with clients in call centers, or think about *Siri*, *Alexa*, and *Cortana*. A game-related example is autonomous game play without human intervention [1].

Automatic approaches to machine learning have a number of disadvantages, though. They are for instance intensively resource consuming, require much engineering effort, need large amounts of training data, and they are most often black-box approaches. This opposes the aforementioned claim of transparency and interpretability, which is of particular importance in educational applications. Also in other sensitive domains, such as medicine or in the context of privacy/data-protection, in-transparent AI is considered problematic and thus the topic is a matter of debate in the AI community, as highlighted by Bologna and Hayashi [25]. Conventional machine learning works asynchronously in connection with a human expert who is expected to help in data preprocessing and data interpretation - either before or after the learning algorithm. The human expert is supposed to be aware of the problem's context and to evaluate and interpret specific datasets. This approach inherently connects machine learning to cognitive sciences and AI to human intelligence.

A different concept is *Interactive Machine Learning* (iML), which allows humans interactively intervene with the logical processes of an algorithm (cf. Amershi, [26]). The goal is capitalizing repeatedly on human knowledge and understanding in order to improve the quality of automatic approaches. The iML-approaches can be therefore effective on problems with scarce or overly complex data sets, when a regular machine learning method becomes inefficient. Combining autonomous algorithms, which usually follow a rather simple set of rules, with expert knowledge and perhaps more fuzzy concepts such as human intuition may facilitate the development of future AI systems The hypothesis of this research is that the combination of both bottom-up machine learning approaches and top-down human cognition substantially improves the effectiveness of smart educational solutions for the assessment and the personalization of digital educational games.

1.3 The Travelling Salesman Problem

The Traveling Salesman Problem (TSP) is one of the most famous combinatorial optimization problems, studied since the 18th century (Laporte, [27]). The challenge is planning the shortest route between a numbers of scattered waypoints while visiting each waypoint (except the first one) only once. Ever since, this problem has become a test bed for the development of new AI methodologies and algorithms in all disciplines, for example in medical research such as DNA sequencing. TSP refers to the problem of finding the most effective (i.e., shortest possible) path between a given set of waypoints. The name "travelling salesman" refers to the problem description where a salesman has to travel a number of cities and return to the starting point. The problem is a NP-hard problem in combinatorial optimization, which means that an algorithm for solving it can be translated into one for solving any NP-problem (nondeterministic polynomial time) problem. NP-hard therefore means "at least as hard as any NP-problem," although it might, in fact, be harder. In other words, for a NP-hard problem a polynomial time algorithm for solving all its cases has not been found by now and it is unlikely that it exists, as pointed out by Garey and Johnson [28]. When humans are facing a TSP, they automatically and intuitively gain a first-sight overview and they can identify certain patterns and global relationships. The psychological foundations can be seen, for example, in the fundamentals of Gestalt psychology [29]. Gestalt psychology, in essence, outlines basic mechanisms how humans mentally create objects on the basis of, in principle, unconnected elements. An example is that humans often perceive two dots and a line as a face. Our hypothesis is that this initial global evaluation of the waypoints and the identification of certain cluster and patterns may give human strategies the edge over the computational approximations. For the present study, we implemented the possibility that humans can intervene in the path-finding process by intentionally altering the pheromone distribution.

1.4 Interactive Ant Colony Optimization

As mentioned, one important task for game AI is pathfinding (e.g., in form of the TSP setting), which for example can be used to control NPCs. For serious games, pathfinding is an important task as well, for example finding the optimal learning path through the elements of the game (including gaming, learning, and assessment elements), as pointed out by Romero and Ventura [30].

The Ant Colony Optimization (ACO) is a metaheuristic approach for solving Optimization problems (including pathfinding) inspired by biological systems such as swarms or ant colonies. ACO has been devised in the last years of the past century and today is intensively studied and applied (Dorigo, Maniezzo, and Colorni, [31]) The behavior of real ants can be used in artificial ant colonies for searching of close-enough solutions mainly to discrete optimization problems. As one of the most successful swarm-based eusocial animals on our planet, ants are able to form complex social systems. Without central coordination and external guidance, the ant colony can find the shortest connection between two points based on indirect communication. A moving ant deposits on the ground a chemical substance, called pheromone. The following ants detect the pheromone and more likely follow it. Specific ant species exhibit more elaborated behavior.

```
procedure ACOMetaheuristic
    set parameters
    initialize pheromone trails
    ScheduleActivities
            ConstructAntsSolutions
            UpdatePheromones
    end-ScheduleActivities
    return best_solution
end-procedure
```

```
start the GAME
        init MMAS
        draw apples
        run 5 iterations
        while (apple left)
            wait for snake to eat apple
            edge=[lastApple][currentApple]
            pheromone-level of edge*5
           run 5 iterations
        end_while
return total path
```

Figure 1. *The left panel shows the general ACO algorithm scheme on static combinatorial problems. The right panel shows the logic of the MMAS algorithm including the human intervention (apple eaten) every five iterations.*

A popular and flexible algorithm is the *MAXMIN Ant System* (MMAS), as described by Acharya [32]. The algorithm is a probabilistic approach for solving combinatorial problems, which can be reduced to finding optimal paths through graphs. It is a multi-agent method inspired by the behavior of ants. The pheromone-based communication of biological ants is often the pre-dominant paradigm used for the computational optimization. MMAS exploits the best tour of an ant, it limits the excessive growth of the pheromones on good tours (which in some cases is suboptimal), by adding upper and lower pheromone limits (min and max). In addition, it initializes the pheromone amount of each edge to the upper pheromone limit max, which increases the exploration of new tours at the start of the search. Finally, each time, if there is a stagnation in some way or no improvement of the best tour for a particular amount of time, it reinitialize the pheromone trails. The specific algorithmic scheme is illustrated in Figure 1 (left panel). After the initialization of the pheromone trails and some parameters, a main loop is repeated until a termination condition (i.e., time limit or number of optimization steps) is reached. In the main loop, first, the ants construct feasible solutions, then the generated solutions are possibly improved by applying local searches, and subsequently the pheromone trails are updated. In technical terms, in the main loop each "ant" constructs a path by successively approaching nodes on the basis of a stochastic selection function which can be described as follows [32]:

$$P_i^k(j) = \begin{Bmatrix} (\tau_{ij}^{\alpha}).(\eta_{ij}^{\beta}) / \sum_{k:\, k \in N_i^k} (\tau_{ik}^{\alpha}).(\eta_{ik}^{\beta}) \text{ if } q<q_0 \\ 1 \text{ if } (\tau_{ij}^{\alpha}).(\eta_{ij}^{\beta}) = \max\{(\tau_{ik}^{\alpha}).(\eta_{ik}^{\beta}) : k \in N_i^k\} \\ 0 \text{ if } (\tau_{ij}^{\alpha}).(\eta_{ij}^{\beta}) \neq \max\{(\tau_{ik}^{\alpha}).(\eta_{ik}^{\beta}) : k \in N_i^k\} \end{Bmatrix}, \tag{1}$$

where $P_i^k(j)$ is the probability that ant k selects the node j after node i, given that this node hasn't been visited before. η_{ij} is determined by the inverse distance from i to the new node j and can be interpreted as the salience of a node. τ_{ik} is the pheromone concentration associated with the link (i,j) and α, β establish weightings for the salience and pheromone concentration. To facilitate path exploration, $q0$ is a pseudo random factor altering node selection.

2 The Travelling Snakesman Game

Our hypothesis is that the combination of the bottom-up MMAS algorithm and human interventions in the algorithm lead to superior pathfinding results than the algorithm alone. For the present study, we implemented the possibility that humans can intervene in the path-finding process by intentionally altering the pheromone distribution. To investigate this hypothesis we developed the *Travelling Snakesman* game, a *Unity3D*-based browser which is freely accessible at https://iml.hci-kdd.org/TravellingSnakesmanWS). This game represents the original TSP by displaying apples on the screen. The human player controls a snake with the goal to eat all apples as quickly as possible (Figure 2). Controls work via mouse or touchscreen inputs. The game is composed of three levels with increasing complexity. High scores for all levels are available on a daily, weekly, and an all time basis.

2.1 Method

For the game we designed three levels (Figures 2 and 3) in terms of the distribution of apples. The levels increase in difficulty, meaning that the amount of distinct clusters of apples decreased. Within each level, the distribution of the apples was rotated to reduce certain effects of the orientation of apples and apple clusters. The game was implemented with Unity3D, the algorithm was implemented for the game in C#. A detailed description of the algorithm is given by Stützle and Hoos [33]. The participants started each level and attempted to collect all apples. When reaching the final apples, the level ended and the participants automatically returned to a main screen. At the beginning of a level, an instance of the MMAS algorithm approximates the solution, that is, the minimal distance among the apples. Since the perfect solution cannot be obtained within reasonable time, these results vary. To avoid delays due to computation times and to establish comparable conditions, the algorithm was restricted to 175 iterations of the pathfinding process. In the course of the human play, the algorithm includes decision of the player every five iterations. Figure 1 (right panel) illustrates the logic of the game algorithm. The human interventions in the algorithmic process are realized by altering the pheromone parameter of the algorithm on the basis of the human control of the snake (i.e., the selected apple) every five iterations of the algorithm. By this means, the decisions of the algorithm are overruled and the pheromone distribution changes accordingly. The algorithm, subsequently proceeds with the new parameters. According to our hypothesis, the wayfinding with human interaction should be superior to the results of the algorithm without the human intervention. To evaluate this hypothesis we compared the minimal distance from five runs of the algorithm, prior to each gaming sessions, with the distance travelled by the algorithm including the human intervention.

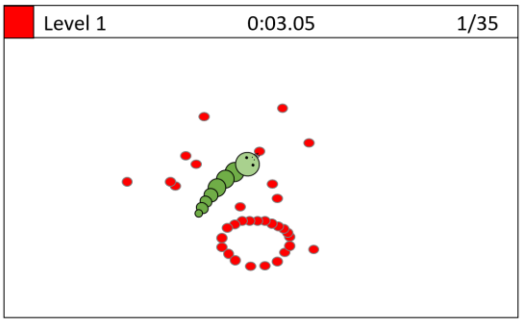

Figure 2. *Illustration of a level of the Traveling Snakesman game*

2.2 Results

In order to investigate the hypothesis, we set up a first exploratory online study. We invited people to play the game and instructed them to play it as effectively as possible in order to improve the high score. In total 95 games were played. In a first step, we investigated the results of the MMAS algorithm (we name it C) with the results of the algorithm including the human interventions (we name it CH). As dependent variable, the distances travelled on the screen were measured.

To quantify the difference between the C and the CH group, we computed an analysis of variance (ANOVA) for the independent variables level (game levels 1 – 3) and group (C, CH). The variable level (ranging from 1 to 3 with an increasing difficulty) is the repeated factor since all participants played the levels consecutively. The ANOVA yielded a significant main effect of the factor level [$F(2, 189) = 79546.172$, $p < .001$]. This result is expected since the levels with increasing difficulty require increasingly longer paths. More important is the factor group, where we found a significant main effect as well [$F(1, 189) = 33.951$, $p < .001$]. At level 1 the mean of group C was 4489802.48 (SD = 109628.351), the mean of group CH was 4,376,090.665 (SD = 94,430.853). At level 2 the mean of group C was 36,281,284.86 (SD = 855,204.253), the mean of group CH was 35,839,124.63 (SD = 722,500.697). At level 3 the mean of group C was 44,247,653.59 (SD = 713,300.268), the mean of group CH was 43,233,333.61 (SD = 865,187.636). Across all of the three game levels, group CH resulted in somewhat shorter distances traveled.

In order to elucidate the differences of groups C and CH more in-depth, we looked into the differences in path lengths between both groups (Table 1, Diff.). Instead of computing the differences in each trial – remember, for each trial, the algorithm approximated the shortest path and in parallel humans played the game and influenced the algorithm with their choices – we computed the differences between group CH and the average of all computer trials (reported as C in Table 1). Given that the path lengths for the three levels are different, for a general comparison, we transformed the distances into a range between 0 and 1 (by [CH – Cmin] / [Cmax – Cmin]), which can be considered as the relative improvement in group

Table 1. *Absolute minimum distances obtained across groups and levels*

	C	CH	Diff.
Level 1	4,242,192.5568	4,215,015.4717	27,177.0851
Level 2	34,178,226.0850	34,680,651.6358	-502,425.5508
Level 3	42,529,746.1429	41,378,863.0008	1,150,883.1421

CH as opposed to the average of group C. The relative improvement for level 1 was 0.1394, for level 2 0.1021 and for level 3 0.0814. One-sample t-tests computed for each level yielded that this improvement is significant for each level. Level 1: $t(38) = 7.519$, $p < .001$; level 2: $t(26) = 4.310$, $p < .001$; level 3: $t(27) = 3.346424$, $p = .002$.

In addition to the quantitative path distances, we looked into distinct differences in the selected paths between humans and the algorithm. Figure 3, shows the results. The red paths were chosen more often by humans as opposed to the algorithm and, vice versa, the green paths were preferred by the algorithm. The more frequent a path was chosen, the thicker is the corresponding line. A specific finding of this graphical analysis is that on average humans tended to prefer other transitions than the algorithm did. Figure 4 (left panel) shows the average step length of the algorithm, humans, and when humans intervene with the algorithm. More importantly, while the mere means of step sizes (distance between two consecutive points) did not reveal distinct differences the distribution of step length differed clearly; humans accepted the by far longest step sizes. Not all human interventions, however, improved the performance of the algorithm. As shown in Figure 4 (right panel), only in about two thirds of the cases, humans could improve the performance; substantial improvements were observed only in about one third of the cases.

In general, the results of this study provide some evidence for our initial hypothesis that humans do choose other connections from one point to another and that they intuitively accept very long step sizes, which may result in an advantage. These strategic differences can improve the computer algorithm to a certain extent, as this study revealed.

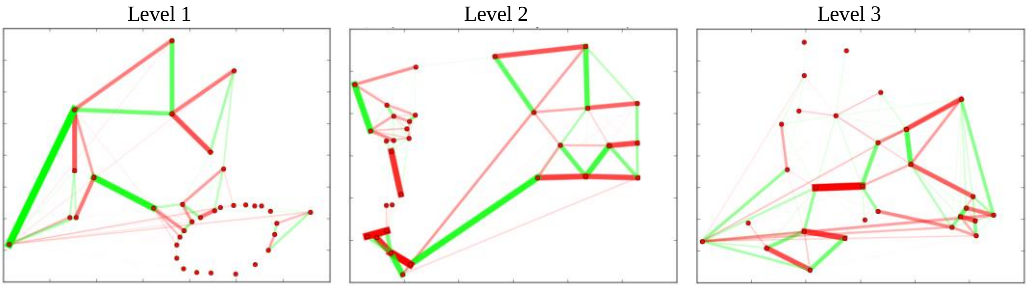

Figure 3. *Path frequencies: humans only (red) vs. ant system algorithm without interventions (green)*

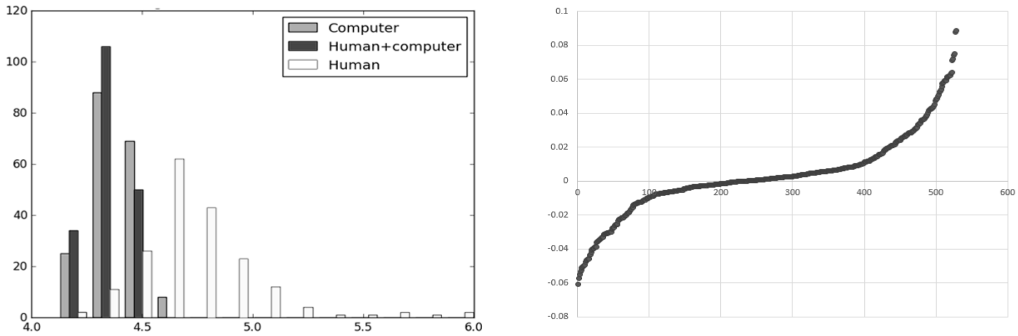

Figure 4. *The left panel shows the ordered frequencies of average step lengths (distance from the current apple to the chosen next one); the right panel shows the effects of human interventions on the total distance travelled.*

3 Application to Serious Games

Our study has confirmed our initial hypothesis that human cognition and intuition can improve - to a certain extent - the performance of ACO in general and MMAS in particular. Further research is needed to elucidate the underlying cognitive mechanisms. This is particularly true since the findings show that only in about one third of the cases, substantial improvement could be achieved. As discussed initially, in serious games “pathfinding” may not only occur with regards to the navigation in the game environment, in serious games oftentimes a pedagogically effective sequencing of game elements is necessary. These game elements may be for gaming purposes, for instructional purposes, or for the assessment of learning progress. Basically, the challenge for adaptive algorithms is to identify optimal and personalized gaming sequences. In the following we introduce one adaptive technology for serious games, that is, Micro Learning Spaces (MLS) and discuss the applicability of the interactive MMAS algorithm.

3.1 Micro Learning Spaces

The main task for such technologies is to guide and support the learner in acquiring knowledge by, for example, informing the learner, intervening when misconceptions occur or the learning progress is unsatisfactory, hinting, or providing the learner with appropriate feedback. In addition, tasks are motivating learners, maintaining immersion, and personalizing the game according to the preferences and needs of the learner. AI and specifically machine learning techniques are capable of identifying important insights from a data-driven perspective. In many serious games, where learning along curricular or at least didactic trajectories is endeavored, bottom-up approaches such as machine learning might not be enough. Accomplishing appropriate assessment and adaptation requires a theoretical top-down perspective on in-game learning processes that enable the game to assess cognitive states (e.g., competence states or motivational states), learning progress, possible competence gaps, or undirected/unsuccessful problem solving strategies.

A prominent approach, described by Kickmeier-Rust and Albert [13, 36] is MLS, which stems from combinatorial *Knowledge Space Theory* (KST) and which accounts for the fact that game-based learning situations, generally, have a large degree of freedom as opposed to conventional learning materials. The approach attempts to interpret all actions of a learner within the game environment in terms of available and lacking competencies or skills. To achieve this, micro-adaptivity combines knowledge structures with *Problem Spaces*. The basis of this concept is decomposing a problem or situation into the collection of all possible and meaningful problem solution states, the objects relevant for a problem, and transition rules, specifying how admissible transitions from one to another problem solving state can occur. Based on the objects and the rules, for each problem solving state a set of admissible actions can be defined. The problem space, in a way, represents a formal model of the game situation and establishes a set of possible paths through this situation. The competence structure establishes a formal representation of the knowledge domain and a set of possible learning paths. For the purpose of a non-invasive assessment of competencies, both types of formal structures are merged by a functional association of problem solving states with a set of competence states. This procedure is equivalent to a Bayesian model, only it operates on the foundations of a KST-type knowledge structures. The approach has been refined and extended continuously, e.g., concerning motivational assessment or interactive, digital storytelling [34]. Also the most recent psychometric advancements of KST models towards *Assessment Structures* and *Assessment Spaces* (cf. Heller, [35]) have been incorporated. These generalize the MLS-type assessment and adaptation to broader and ill-defined domains such as medical diagnostics, general psychological testing, or game environments with a large degree of freedom [36].

3.2 Serious Game Structures

Systems that are based on MLS operate with a set of game elements (or game situations), which are characterized by their educational contents (e.g., the competencies that are taught or tested), by their problem solving challenges (e.g., to apply certain competencies to unravel a riddle), and by their narrative function in the game (e.g., the transition from one level into another). All these elements have an internal structure. The educational contents usually follows a conceptual sequence (a curriculum) and thus there are prerequisite relationships between the elements. For example, it might be necessary to have acquired certain competencies before others can be learned. These relationships pose a hierarchical, combinatorial structure (as it is shown in Figure 5). Equally, a formal problem solving process consists of a start state, an end state, and a set of rules. The rules determine a set of possible sequences to solve the problem. This, in turn, imposes a structure that is conceptually identical to the educational structure. Finally, the storyline of the game imposes a logical narrative structure among the various game elements. When combining these structures, a large set of triples (of competencies, problem solving steps, and game elements) arise, which determine the options in the game. The combined structure, the so-called learning space, is the set of all possible and necessary paths through the game. An MLS system uses this structure as the foundations to adapt the game play and to sequence the game elements. On the basis of the learning space, the system can assure that (if it is possible at all) the game's story line can be concluded without gaps and inconsistencies while reaching the learning objectives and mastering the in-game challenges. A simplified learning space is shown in Figure 5. This figure reads from bottom (the start state of the game) to the top (the desired end state). A formal elaboration of the approach is given by Kickmeier-Rust [37].

An optimal adaptation to an individual player/learner requires the identification of the right path through the game. For example, it is necessary for an adaptive system to avoid that a learner takes a story paths that leads into a dead end in terms of accomplishing the learning goals. Also, some paths maybe more effective (or more complete) than others. While in non-adaptive games, this sequencing is done by instructional designers and game designers, adaptive system such as MLS are based on the underlying structures, which are developed by experts. Moreover, in real game applications the number of possible game elements and resulting paths might be huge. AI can help, to improve the adaptation logic by providing a solution for identifying the best possible path. As for the TSP, this identification is an optimization problem. Insofar, finding the right path is comparable to the TSP, we have discussed above. Equally to the Travelling Snakesman study, we argue that incorporating human decisions, in the algorithm process may improve the performance of the algorithm and therefore the quality of adaptation and personalization in serious games. MLS-type structures (Figure 5 illustrates a simple and small one) may be composed of hundreds and perhaps thousands of elements. Since a key goal for adaptive technology is making (learning) processes more effective, algorithms attempt to identify the most effective path through these structures. Rastegarmoghadam and Ziarat [38] emphasize, for example, that swarm intelligence and ant colony optimization may provide an effective method for finding optimal learning paths based on self-organization. Reducing the "travel costs" translates into more learning paths in terms of time and efforts. As the equivalent to the TSP, passing through all required nodes can optimized in terms of time/effort instead of "length". The present study provides some indications, that enriching these algorithms with human interventions to the algorithm, not only by pedagogical consideration, can improve personalization of tutoring systems.

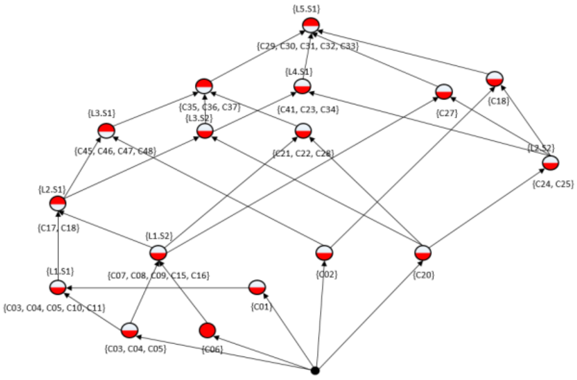

Figure 5. *A simple MLS-type learning space, which is the lattice of meaningful and admissible paths through a learning game; In the example the game is composed of five levels L (including sublevels S) and 48 taught competencies C. Nodes with missing labels indicate an incomplete coverage by the game.*

4 Conclusions

Serious games are a mainstream educational medium and the repertoire of existing games is extremely broad. Growing communities and platforms successfully aim at making the genre ubiquitous. One example is the Serious Games Information Center (https://seriousgames-portal.org), hosted by the Technical University of Darmstadt. A number of studies and meta-reviews yielded that a serious game's success depends on its capabilities to engage learners and to provide them with personalized gaming and learning experiences [2, 3]. Therefore, theoretically sound mechanisms for gaining insights and a certain level of understanding of learning and gaming processes by the game, as an autonomously acting instance, are crucial. This refers, for example, to sound psychometric methods for an in-game assessment – ideally in an unobtrusive, stealth manner [5]. This refers also to leading edge AI techniques, which increasingly become part of the tool sets of modern serious games [18]. Serious game AI can and must support learners making their way through the game environment and the narrative, help them overcoming challenges and solve problems in a constructivist sense, and – ultimately – help them reaching the game's "serious" goal. In this paper we introduced the MMAS as a means of optimizing a combinatorial problem, in our case the TSP. While the algorithm as such can approximate solutions, we argued that human cognition or intuition may improve the performance of the algorithm. The foundations for an improvement are likely based on mechanisms such as Gestalt principles, which allow humans to get a quick overview of the entire scenario and to combine elements to distinct clusters. In the presented online study we could find a performance increase when human decisions influenced the algorithmic process. In the context of serious games, we find complex wayfinding problems as well. Usually we have a set of gaming elements, which might be a certain task or a certain level, well-defined challenges requiring human problem solving, educational elements (e.g., the competencies to be taught) following a certain instructional, and a narrative tying all the elements together to a meaningful and exciting story. This dazzling array of interrelated elements, however, is a complex problem for an appropriate adaptation and individualization of games. We argued that optimization solutions such as the MMAS can support the adaptation process. Top-down human interventions in the algorithm, for example by pedagogical expert knowledge, can improve the performance. In the present paper we could demonstrate a beneficial effect by simply adjusting the salience and pheromone concentration parameters of the algorithm. Of course, there are other algorithms. In the context of games, the A* search algorithm is popular (cf. Cui and Shi, [39]). There are pros and cons to the various algorithms, the MMAS appears more flexible in settings with varying costs functions, which is determined by the human interventions in this study.

Serious games can profit from the approach by making automated personalization, for example the sequencing of learning opportunities, more intuitive and also more effective. A common approach for providing personalization in serious games is Competence-based Knowledge Space Theory [40]. As Melero and colleagues [40] point out, the development of underlying domain models by human experts is costly. An algorithm that supports the identification of effective learning paths can facilitate the authoring process substantially [41].

Future work will consider comparing the performance of different algorithms with humans in their loop. Also, future work will increasingly develop path finding scenarios on the basis of psychological theories. In addition, the approach will be prototypically implemented in the well-documented *80Days* Geography learning game (http://eightydays.cognitive-science.at/). This game appears suitable since it features the aforementioned competence structures, problems spaces, and an interactive storyline.

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