Sharing Behaviors in Games

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Abstract: User generated media highlights sharing: Sharing videos, images and texts in social media, as well as sharing character outfits and maps in games. However, behavior is one of the aspects that are not shared. The aim of this study is to show how user generated behaviors can be shared in different types of games. The game genres for this study are educational games and fighting (sports) games. The examples about sport games and educational games are based on MindFarm AI technology that enables end users to construct human-like behavior by only teaching. MindFarm emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and complex relations between these concepts and experiences. Phenomena when the mental structure change is called learning. In the near future user-generated behaviors can be developed and shared, as all other user-generated content. According to examples on this study, game developers can design extensions that enable users to easily construct behaviors. From a game consumer point of view, the most interesting part is in developing behaviors, sharing them and finally playing with them, or against them.

Key-Words: Artificial Intelligence, Behavior, Games, User modeling, User generated content, User experience

1 Introduction

User-generated content, such as the choice of a game character's outfit, its textures and clothing, as well as editing game scenarios, has been an integral part of games for a long time. It seems that users require features and activities that can be personalized and shared. However, there is no such interest in sharing behavior, strategies or game character personalities. All in all, this is not completely because of a lack of technologies for modeling and sharing AI -related contents [1].

Unlike visual objects, behavior is a complex phenomenon. This complexity has set limits for developing AI's that could enable behavior construction without programming or scripting. In fact, AI programming traditionally requires not only programming skills, but mathematical skills also. Another point of discussion is whether game AI is about intelligence or behavior. Baekkelund [2] argued that game AI is far more difficult to determine than academic AI. Furthermore, while academic AI research focuses on perfect or optimal behavior, game AI should be entertaining: Game AI is allowed to cheat or be 'stupid' in order to achieve the illusion of intelligent and entertaining behavior. In fact, it is easy to build the perfect opponent; the challenge is to build an entertaining opponent [3].

Sports behavior modeling is challenging. Several games have received negative feed-back related to unrealistic non-player character behavior. Furthermore, in some multi- player games it is relatively easy to guess when one is playing against AI and when one is playing against another human player. On the other hand, the construction of human-like behavior in, e.g. football and hockey is very challenging. Even steering behaviors are surprisingly complex [4]. One other interesting approach can be found in Forza Motorsport, a game in which AI can learn to play like the player does in terms of driving patterns.

However, when discussing learning and behavior, we have to make a distinction between behavior as cognitive behavior and behavior as scripted behavior.

Behavior modeling has a long research background: Neural and semantic networks, as well as genetic algorithms, are utilized to model a user's characteristics, profiles and pat-terns of behavior in order to support or challenge the performance of individuals. Behavior recording have been studied and used in the game industry for some time. In all recent studies the level of behavior is limited, more or less, to observed patterns. [5][6][7].

In this study, user behavior, competence and learning were seen as Semantic (neural) network that produces self-organizing and adaptive behavior/interaction. The AI technology developed, emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and relations between these concepts. Phenomena when the mental structure change is called learning.

In terms of constructive psychology of learning, people actively construct their own knowledge through interaction with the environment and through reorganization of their mental structures. The key elements in learning are accommodation and assimilation. Accommodation describes an event when a learner figures out something radically new, which leads to a change in his/her mental conceptual structure. Assimilation describes events when a learner strengthens his/her mental conceptual structure by means of new relations [8].

The novelty value of this study is in approach: to build technologies that enable easy construction of intelligent and human like behaviors.

2 Research objectives and method

The aim of this study is to show how user generated behaviors can be shared in different types of games. The game genres for this study are educational games and fighting (sports) games.

The challenge/novelty of the study is in the game settings: In order to share user generated behaviors, we should have a computational model that can be

1. easy to construct (user experience point of view)
2. extensible ad scalable (useful for game developers)
3. transferrable and reusable

In educational game the behavior model is about mental conceptual structures. In sports games - fighting games in this case - character behavior is not about knowledge; it is about strategy and decision-making.

As we know, behavior is a consequence of learning, to some extent. The general assumption is that AI that can learn conceptual structures can learn strategies. The study can be seen as being a traditional design study with iterative cycles. The procedure of development was limited to the following:

1. Define what kind of activities are observed and taught in these cases
2. Construct interface for teaching behavior (according to definitions)
3. Evaluate behavior and decisions in terms of their entertainment value.

Evaluation is not meant to be done in terms of cognitive sciences: it is only done in order to evaluate the usefulness of the method.

The examples about sport games and educational games are based on MindFarm AI technology that enables end users to construct human-like behavior by only teaching. MindFarm emulates the human way to learn: According to cognitive psychology of learning, our thinking is based on conceptual representations of our experiences and complex relations between these concepts and experiences. Phenomena when the mental structure change is called learning.

The MindFarm AI technology is based on the author's previous work: research articles have been published from the point of view of cognitive science [9][10] and from a technological point of view [11][12].

3 Results

3.1. Sharing behaviors in educational games

In AnimalClass a learner can teach conceptual structures in mathematics, the sciences, languages and arts to virtual pets (teachable agents). After teaching, players can send (share) their AI's to different competitions. AnimalClass is based on the theories of the cognitive psychology of learning: conceptual learning, inductive learning and conceptual change.

The pedagogical idea of Animal Class is to put a learner (player) into the role of a teacher. The background of the game is in Learning by Doing, Learning by Teaching and Learning by Programming. In Animal Class the player has complete freedom to teach the virtual pet however s/he wants, even wrongly. This possibility of teaching wrongly is a crucial feature in order to enable learning away.

At the beginning of the game the player got his/her own virtual pet that does not know anything. Its mind is an empty set of concepts and relations. The pet learns inductively: Each teaching phase increases and strengthens the network of concepts. When the pet achieves a semantic network of a certain structure, it can start to conclude. In Animal Class teaching is always based on statements constructed by the player. The virtual pet answers according to its previous knowledge. If there is no previous knowledge, it will guess. The player then tells the pet if the answer is correct or not, and based on this, the pet forms relations between concepts.

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An interesting part of teaching is the possibility of teaching wrongly. Sometimes the wrong teaching was not due to low skills: for example at the beginning of geometry game, some pupils tried to teach colors instead of the expected shapes. In order to support reflective thinking, there was a brain icon, (fig 1) that describes the quality of learning. If the quality increased, the brains got bigger, and if quality of learning decreased, the size of the brains got smaller. If the overall teaching was wrong, the brains were replaced by a cactus to show the player that he was doing something completely wrong. This kind of wrong teaching could be corrected by teaching correctly long enough to override the wrong learning.

In fig. 1 the player has constructed a question which consists of two triangles and one rectangle. When the question is ready, the player asks the octopus by clicking the 'ask' -button (balloon with three question marks). The octopus answers according to its previous knowledge.

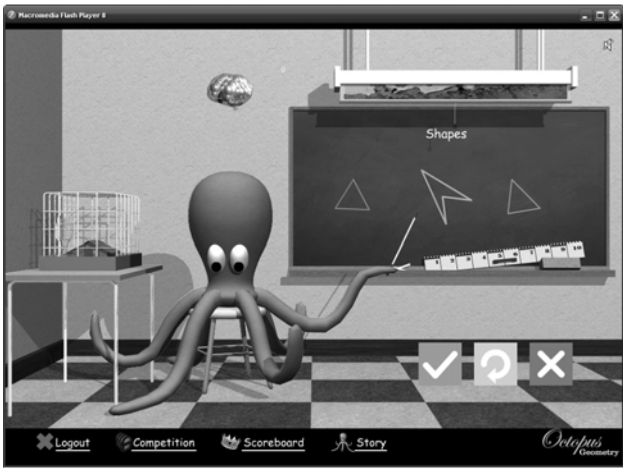

Fig. 1. Question construction and judging in Animal Class, the Pre-School Geometry Game.

After the octopus has given its answer by pointing out the shape it thinks does not belong in the group, the player should judge the answer: if the answer is correct, the player should click the green 'correct' -button. If the answer is false, the player should click the red 'wrong' -button. If the player notices that he has posed an impossible question or is uncertain, the question can be cancelled by clicking the yellow 'cancel' -button.

The teaching itself was found to be motivating. Even so, most pupils expected something more than just teaching. Therefore, a quiz challenge called the "Treasure of the Caribbean Pirate" was included into game as a competition between the pets. In the competition the game AI uses the same semantic networks that were taught in the classroom. In the competition a player can challenge his/her friend's octopus to play against him/her. Because all semantic networks are stored in a game server, a player can challenge opponents even if they are not online. The competition (fig. 2) is based on mechanics similar to teaching. The octopus needs to select which of the shapes does not belong in the group. Both octopuses' answer the same questions at the same time according to taught knowledge.

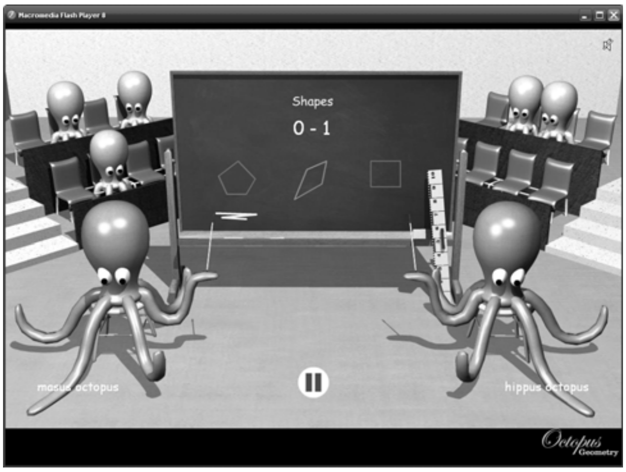

Fig. 2. Competition in Animal Class, the Pre-School Geometry Game.

From behavior sharing point of view, the children feels easy to teach their game characters. Even 6 years old preschoolers could easily taught their virtual pets. Competing against friends' pets were the most fun in the gameplay.

In some cases the children were confused when their virtual pet could be inside several friend’s gameplay at the same time. Furthermore, some children couldn’t understand, how the gameplay could continue in their friend’s computers, though they shut down their computers. However, all of the players did understand the idea of sharing game character’s behavior. Furthermore, they were very interested in seeing their character in another game. This supports the assumptions that sharing behaviors can be successful in games.

3.1. Sharing behaviors in sports games

Fighting games provide a relatively straightforward one-against-one -context with numerous strategic decisions. A one-against-one -game is a simple enough starting point when modifying an AI to a completely new context. For example, if a problem space consists of 12 players, as in ice hockey, the AI requires a great amount of additional teaching before it has a clue about the players or the intentions of other characters.

Behavior model is learned with versatile approaches: Pattern -based methods focuses on a character's movement patterns, such as: "action A ' action B ' action C". In other words, the next action is calculated as a probabilistic model. In this model, we do not take the opponent's actions into account. Another approach is Stimulus-Response -pairs, for example "stimulus=attack, response=blocking". Contrary to the pattern -model, the stimulus-response model does not have a history. A third possible approach is statistical: in accordance to the history, "what is a probable action against a certain opponent". This can be referred to as spots betting: "in accordance with its history, this team will win".

In all cases, the most important feature is feedback: what is the success of such activity? Without the feedback function, the AI would definitely not produce entertaining behavior.

When starting points were summarized, the AI's observation needs were defined as follows: AI should learn patterns of activities, stimulus-response pairs and opponent statistics. All this should be supported by feedback data. The teaching/observation environment was designed as a web-form in order to support easy usability. The teaching tool can be used without any background material, but in this paper, the teaching is based on real video material. The idea is that a user can have two open windows (Figure 3): a window for video material that he/she wants to use in the background, and another window for the teaching tool.

A user makes observations in terms of patterns, stimulus-responses, opponents and success from video footage. Each activity is recorded one by one (fig. 3). In this sense, the recording is relatively time-consuming and requires patience. When comparing this teaching tool to the teaching in AnimalClass, it should be noted that teaching this AI is too difficult for small children. In any event, most fighting games are forbidden for users who are under the age of 15 years.

In this study, we decided to focus on Taekwon-Do, because of the relatively small number of activities during a fight. Furthermore, in Taekwon-Do, the rules define successful actions in a way that can be clearly seen. The person behind the virtual character's behavior is four times World Champion, Ismo Mäkinen. Ismo's behavior was taught in accordance with three one round fights. In reality, teaching should be based on more observations. In this case, it was desirable for the mental conceptual model (AI) to remain as small as possible in order to produce readable visualizations of semantic networks behind decision-making. Teaching takes approximately 40 minutes.

Fig. 3. Teaching an AI in accordance with real world material.

In fig. 4, the semantic network, controlling virtual character behavior, is partially visualized according to stimulus-response pairs, patterns of actions and opponent statistics. When focusing on patterns (fig. 4), we can estimate the behavior as a continuous process. Each node represents an action (a kick, a punch, blocking, moving) and vertices represent the dependencies between the actions. Each vertex does have a weight that is used when computing the probabilities between transitions. What is remarkable is, that the number of nodes is relatively small compared to number of vertices (relations). This is because in modeling, all of the concepts are unique and they can have numerous relations under opponent-, pattern- and stimulus-response labels. This complexity makes, not only visualizations difficult to read, but the decision-making algorithm is also dependent on estimation functions. In this study, we are focusing only on a general framework.

In brief, Ismo's fighting behavior, in terms of patterns and according to our teaching, is relatively straightforward: jabs and round kicks.

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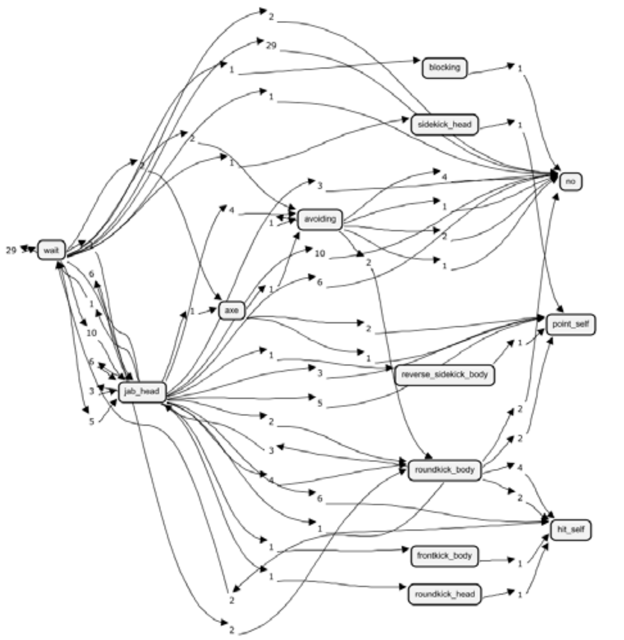

Fig 4. A pattern -related semantic network for a user-generated character's AI.

When all three layers of different behavioral information are summarized, we have a relatively detailed probabilistic model of behavior. In this case the teaching is done in detail and the model could be interesting in terms of sports science. However, in this study, we are not determining how well the model fits reality. We are focusing on intelligent, believable and entertaining behavior.

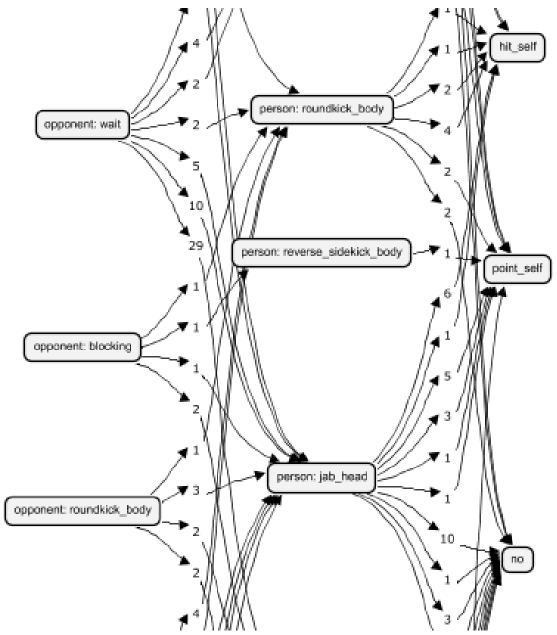

Fig. 5. A partial stimulus-response -related semantic network for a user-generated character's AI.

Ismo's stimulus-response -map (fig. 5) is far more interesting from a game behavior point of view. In short, we can see that jabs are thrust under almost all conditions (stimulus), while round kicks are done under limited conditions. Furthermore, the probability of getting points is high with a round kick, but is this due to the round kick or because of starting conditions? We could produce interesting, versatile behavior for game characters in keeping with this model.

In order to evaluate believable behavior, a character's decision-making needs to be simulated. Simulation requires information about previous actions and the opponent's current action (stimulus) in order to compute probable responses. The simulation tool orders the most probable responses. In testing, the wait -action got too controlling a role, which means that a new estimation function to control wait's and pauses should be designed in future studies. This was partially due to the teaching. Wait cases were labeled as 'wait' whether they were strategic wait's or pauses in activity.

Comparisons of similarities between user-generated AI and real behavior (absolutely believable) were made by comparing the responses given by AI to responses observed from another of Ismo's fights. This fight was not one of those that had been used as teaching material for the AI. In figure 7 the use of simulation is explained in more detail.

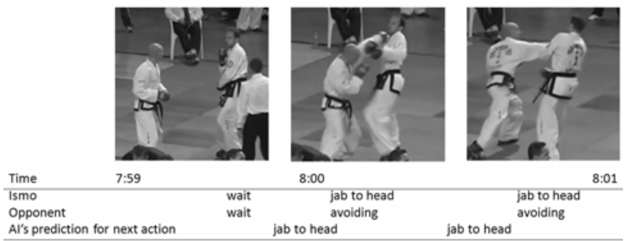

Fig. 6. Example: Photos of actions and a timeline with Ismo's actions, the opponent's actions and the AI's prediction of the next action.

In fig. 6 an action starts with a wait-action. According to the AI, the most probable non-wait action by Ismo is 'a jab to the head', which actually was the next action. After this, the most probable action by Ismo according to the AI is 'a jab to the head' again. In this section the AI manages to produce believable behavior.

After the whole fight was simulated, more than 85% of the real world responses are mentioned in the simulation tool list. Furthermore, nearly 70% of the most probable responses (according to AI) were really Ismo's responses in the real fight. This result is promising in terms of entertaining and believable behavior.

In terms of behavior sharing, this kind of modeling enables completely new way of playing games: Use is no longer seen as end-user, but more like co-producer. When AI's can be easily taught and shared like video clips today, the expectations of human-like AI behavior [3] can be partially fulfilled. The possibilities of behavior modeling do not limit on sports games. In fact, in certain level all games, even games like Pac-man can apply shared behaviors.

4 Conclusion

In the near future user generated behaviors can be developed and shared as all other user-generated content. Furthermore, game developers can design interfaces that enable users to teach versatile behaviors. User-generated behaviors can, e.g. replace AI controlled opponents or extend player's own team. Taught behavior model could be shared on the web. Games and/or developers can upload user-generated behaviors either as AI updates and extensions, or in a development phase. From a game consumer point of view, the most interesting part is in developing behaviors, sharing them and finally playing with them, or against them. Of course, simulated battles could be easily constructed within such a framework.

According to studies, users can relatively quickly and easily teach behavior to a game character. Furthermore, it has been determined that the character's behavior or competence is relatively similar to behavior in the real world, which means that character behavior is believable. As mentioned earlier, the some of the comparisons are made only in terms of being believable behavior. One future branch of research could be in the field of applied sports science. It would be interesting to study how useful this kind of behavior modeling is for athletes and their coaches. What if sports media consumers and fans could be used as observers? By committing and rewarding the audience in this way, a specific sport business would most likely increase its entertainment value.

This study was done in order to study the possibilities of conceptual learning in educational games and in sports games. The similarity between an artificial behavioral model and real world behavior shows the strength of the framework in producing believable behavior. One recognized challenge in applying complex computing to game AI's is time: game AI's are expected to be fast; confusing pauses are not allowed. This means that the speed of AI must be increased. After this, the user generated AIs are ready to be embedded into a "real time" game application.

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