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Adapting Playgrounds using Multi-Agent Systems

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Abstract

This paper introduces an approach on how versatile, dynamic and adaptive playgrounds can be developed using multi-agent systems (MAS), artificial intelligence (AI) and Playware technology. By modelling the children and the Playware playground into a MAS, knowledge about the children's favourite playing behaviour can be acquired. Experiments with children were conduced in order to record their playing behaviours on the Playware playground, which consists of tiles capable of sensing and actuation, and having abilities to communicate with neighbouring tiles. An ANN capable of classifying the children's behaviour within eleven categories (i.e. favourite playing behaviour) was trained using a subgroup of the children. Validating the ANN against the remaining children's behaviours, **93%** were correctly classified. An adaptive playground was implemented utilizing the ANN in classifying the children's behaviour real-time and thus allowing for the children's interest in the playground to be maintained and/or increased by using appropriate adaptation strategies.

1 Introduction

There exists an alarming tendency in the European population today with an significant increase of obesity related problems. The prevalence among children is as many as one in four affected in certain regions. Childhood obesity being an acute health crisis is a substantial risk factor and can lead to chronic non-communicable diseases. New approaches are needed to address the challenge of preventing obesity, particularly in the younger generations (Force and for the Study of Obesity (2002)).

A novel approach which encourages physical activity amongst children and youth is *Playware* (Lund and Jessen (2005), Lund et al. (2005)) which introduces technologies known from robotics, artificial intelligence and multimedia into play equipment. Playware is intelligent software and hardware which aims at producing play and playful experiences amongst its users. Furthermore, *Ambient Playware* is defined as Playware with ambient intelligence characteristics. Thus, Ambient Playware can be personalized, it is adaptive and it is anticipatory. This allows for an integration of Playware technology into the environment so that users can freely and interactively utilize it. We believe that future playgrounds can be made of several building blocks of Ambient Playware, which placed in a real physical environment, allows for the interactions with the building blocks to merge with the characteristics of the real world to letting creative and active plays emerge amongst its users.

Playware playgrounds contrast from today's computer games, which allow users to playing through virtual characters, by allowing the users to *be* the characters. However, the users can physically move and interact with and within the environment which differentiates Playware from virtual and augmented reality environments. By doing so, Playware playground merge the versatile, dynamic and adaptive behaviour of today's computer games with traditional physical playgrounds which ultimately can help in keeping the children's playing interest in the playgrounds and therefore proportionally increase their physical activity — i.e. the playground could adapt according to the children's behaviour.

2 Children, Playgrounds and Multi-Agent Systems

In order to develop versatile, dynamic and adaptive Playware playground knowledge about the children's favourite playing behaviour on the playground is necessary (Derakhshan and Hammer (2005)). This could be knowledge about favourite moving patterns, such as jumping, running, doing somersaults etc. Having this knowledge, it could be utilized in adapting the playground into favouring these behaviours[1].

Since all children are different their individual interest in the playground are also more or less different. Hence, in order to adapt the playground to maintain or even increase children's playing interests, the playground should be able to adapt accordingly. This implies that it must be possible to recognise and/or predict the behaviour of a child playing on the playground. However, when several children are playing together on the playground, the playground needs to be adapted in order to maintain several interests; thus, also the collective behaviour of the children needs to be recognised and/or predicted.

In order to recognise and/or predict children's interests the Playware playground is modelled in a multi-agent system. Using the VOWELS paradigm (Demazeau (1995)) MAS can be considered consisting of agents, environment, interactions and organisations. Thus, the Playware playground can be mapped into a MAS as shown in figure 1 where the children are considered as being agents, the playground being the environment, the interactions are those between the children and the playground (i.e. agent–environment interactions) or other children (i.e. agent–agent interactions) respectively. For now, only the agent–environment interactions will be considered and will be referred to as the agent's "situation". However, in future development, parts of the playground (e.g. the tiles) could become themselves agents in the system, and thus yielding for an extension of the agent–agent interactions in the system. Finally the two children playing together is the organization. Several organizations could exist if e.g. groups of children play independently of each other on the playground (Derakhshan et al. (2006b)). In this paper, the MAS is assumed only to consist of one organization.

[1]E.g. if a child is playing the "smash game" (Headon and Curwen (2001)) on the playground, a location is indicated which the child has to "smash" by e.g. jumping on this location. If however the child playing the "smash game" favours running instead of jumping, the locations that the child has to smash should be adapted to be located farther apart increasing the use of the running behaviour in the game — i.e. the child's favourite behaviour.

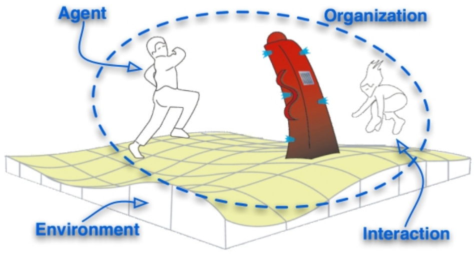

Figure 1: Mapping the Playware playground into a MAS.

2.1 Modelling the Children

Considering the children being the agents, the agents are supposed to be cognitive. That is, the children's behaviour, being a sequence of actions, is more or less intentional. Prior to performing an action, the child needs to deliberate according to its "playing intention" and its perception of the environment. However, the actions available to the child are limited to the agent–environment interactions of the Playware playground. In turn, these interactions define the possible behaviours of the agents which inhibit the system (Shoham et al. (2003)), i.e. the various behaviours children's.

Having several children playing together on the playground, collective behaviours occurs according to how the children organize themselves; that is, the organisation defines the role of the children. This agent–agent interaction originate from the children's "joint playing intention" on the playground. However, it is assumed in this paper, that the agent–agent interactions are given by the agent–environment interactions on the Playware playground.

2.2 Modelling the Environment

Before the agent–environment interactions can be defined, the environment needs to be modelled. The Playware playground consist of several building blocks, namely tangible tiles as illustrated in Figure 2 (Lund et al. (2005)), which allow for different playground morphologies according to the assembling. The assembled playground contribute to the play (e.g. by audio and/or visual interaction) allowing an interesting and dynamic storyline to emerge with which the children can merge with their own imaginary stories (Singer and Singer (1990)).

The tiles dimensions are $21cm \times 21cm \times 6cm$ (width, height, depth) and each includes: An Atmel ATmega128 microcontroller, a 4-way bidirectional communication bus for local communication

Figure 2: Four tangible tiles assembled into a playground. The light output is placed in the upper right corner of the tile while the "bump" indicates the position of the force sensor.

with neighbouring tiles at RS-232 level, four bright Light Emitting Diodes supporting output at different intensities of the colours red, green and blue and a Force Sensitive Resistor (FSR) sensor (FlexiForce A201) which can measure user interactions at dynamic levels.

Having the processing capabilities in each tile, and the local communication, the potential for each tile to become an agent is apparent.

2.3 Situating the Agents

Three physical parameters can be measured from the interactions with the tiles on the Playware playground, namely the force applied on a tile in a movement (p), the Euclidean distance travelled in a movement (d) and the duration of the movement (t) (Derakhshan et al. (2006b)). The three parameters are illustrated in Figure 3.

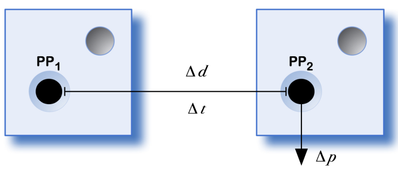

Figure 3: The three physical parameters that can be measured on the Playware playground — the movement travels from PP_1 to PP_2.

Combining these parameters the agent–environment interactions (i.e. the possible actions of a child) on the playground is defined. Having two states for each parameter, i.e. soft or hard force applied, near or far distance travelled and slow or fast duration of movement, eight actions are possible as listed in Table 1 and named according to their descriptive nature, e.g. a "walk" action has a soft pressure (contrary e.g. a "step" action), is at a near distance (contrary e.g. a "run" action) and is slow (contrary e.g. a "run" action). The states of the actions are defined according to appropriate predefined threshold values.

Table 1: The eight actions defined according to the force (p), distance (d) and duration (t) parameters.

Action	Δt	Δp	Δd
Walk	slow	soft	near
Touch	fast	soft	near
Step	slow	hard	near
Tug	fast	hard	near
Stretch	slow	soft	far
Stroke	fast	soft	far
Jump	slow	hard	far
Run	fast	hard	far

3 Adapting the Playground

Adaptation can be embedded on the Playware playground by considering the three phases as illustrated in Figure 4: *Observation* of the children's play, *Classification* of the children's behaviour and *Adaptation* of the playground. In the adaptation phase, an appropriate strategy must be chosen according to the children's interactions with the environment; thus, several different behaviours of the children need to be learned in order to apply the best adaptation strategy that promotes the activity level of the children.

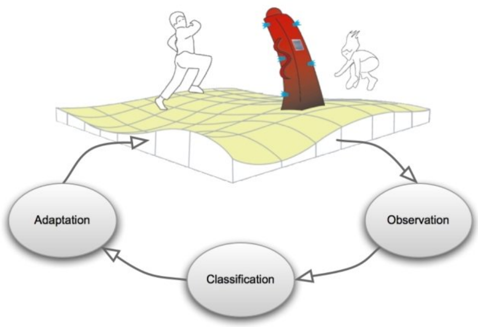

Figure 4: The adaptation cycle consisting of *observation*, *classification* and an appropriate *adaptation*.

3.1 Observing Children's Play

To get knowledge of children's behaviour on the Playware playground experiments were conducted. A

Playware playground, consisting of 36 tiles arranged in a 6×6 grid, capable of collecting data of the children's interactions was used together with video recordings. Prior to the experiments none of the children were informed about how to interact with the playground nor were they informed about the implemented game. By doing so, and by setting the experiments in a neutral environment as e.g. the children's kindergarten (see Figure 5), the experiments attempt to capture the blank intentions of the children.

For the experiments a game named "Bug Smasher" was implemented on the playground, which encourages the children playing to smash some bugs (indicated by the LEDs) which are wandering around the playground. The game has a number of internal states, interactions and feedback in accordance with the actions listed in Table 1.

Figure 5: A 5 year old child playing a game on the Playware playground.

Two types of experiments were conducted; an *individual* experiment trying to settle the children's initial intention and a *group* experiment trying to settle the children's joint intention when playing together. In both experiments an external observer recorded the behavioural description of the children – i.e. classifying the cognitive agents (or, children) internal architecture according to their external description (Demazeau and Müller (1991)).

A total of 46 experiments were performed each lasted for 5 minutes in order to allow for the children's behaviour to evolve. All the children which participated were Danish and distributed among 27 males and 19 females. Two age groups were represented within the experiments; 37 were 5-6 years of age while 9 were 10-13 years of age.

In the individual experiments, three general observations were made from the children playing by the external observer (listed in Table 2): A *Playing* behaviour where the children interacted with the "Bug Smasher" game through the environment. A *Not Playing* behaviour where the children did not interact with the "Bug Smasher" game, but still interacted with the environment according to their intention. Finally, a *None* behaviour categorises the children who did not interact with the environment (i.e. their behaviour could not be measured by the playground). In total 17 children were *Playing*, 13 children were *Not Playing* and 8 children had a *None* behaviour.

Table 2: The general observation of the children's behaviour during the individual experiments.

Observation	5-6 years of age	10-13 years of age
Playing	10	7
Not Playing	13	0
None	6	2

In the group experiments, the children (only 5-6 years of age) were allowed to play two at the time on the playground. All the children participating had a *Playing* behaivour; however, two collaborative behaviours were noted by the external observed (listed in Table 3): A *Competing* behaviour where the children competed on squeezing the bugs in the environment. And *Cooperative* behaviour where the children cooperated on squeezing the bugs in the environment. However, the behaviour of the children would sometimes vary from being initially cooperative to occasionally competitive, e.g. some of the children pushed each other competing on squeezing a bug (see Figure 6). In total 3 groups were in general *Cooperating*, 1 group was in general *competing*, and 0 had a *None* collaborative behaviour as listed in Table 3.

Table 3: The general observation of the children's behaviour during the group experiments.

Observation	5-6 years of age
Cooperating	3
Competing	1
None	0

3.2 Classifying Children's Behaviour

The next phase in embedding adaptivity on the Playware playground is to classify the children's behaviour. The classes of behaviours can be defined according to the observations made by the external observer, excluding the *None* behaviours as these are unmeasurable from the playground. The behaviours are classified, as being from either an individual child or a group of children playing. If it is an individual child playing, it is classified within the two age

Figure 6: Two 5-6 years old girls competing on squeezing a bug in the group experiment.

groups (i.e. younger and older) and if the child is *Playing* or *Not Playing*. If a child is observed as *Playing* eagerly the class “Playing Fast” is used. On the other hand, if the child is barely *Playing* the class “Playing Slow” is used. If the child is *Not Playing*, but has a deliberate behaviour (i.e. the behaviour intentional) the class “Not Playing Continuously” is used. If the child is *Not Playing* in a chaotic manner (i.e. the behaviour is somewhat unintentional), the behaviour is classified as “Not Playing Discontinuously”. Groups of children playing are classified according to if they are interacting with the game or not (i.e. *Playing* or *Not Playing*). If the children are *Playing*, they are next classified in accordance with their social behaviour; thus, “Playing Cooperating” and “Playing Competing” if the children are cooperaing or competing on squeezing the bugs respectively.

Thus in total, the eleven categories illustrated in Figure 7 were observed by the external observer, and can be used to classify the behaviour of the children on the Playware playground.

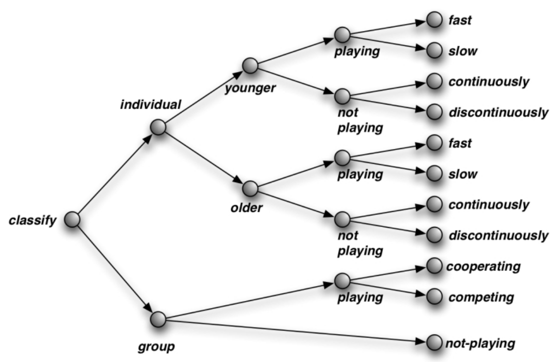

Figure 7: The eleven categories which classifies the children’s behaviours on the Playware playground.

An artificial neural network (ANN) capable of classifying the children’s behaviour according to eleven classes defined by the external observer has been designed. The architecture of the ANN is shown in Figure 8. The ANN inputs the child’s perceptions of the environment and the corresponding actions performed by the child. The perceptions consists of the *direction* the child is moving on the playground, the pressed *tile’s state* (i.e. the colour of the current tile) and the *neighbourhood state* (i.e. the colours of neighbouring tiles). The action input correspond to the three physical parameters (see Figure 3), that is; the *force* applied on the tile (p), the Euclidean *distance* travelled in the movement (d) and the *duration* (t) of the movement. To classify the behaviours defined in Figure 7, several perception/action inputs from the playground must be considered in sequence. Thus, history is added to the ANN as additional input neurons. History can be thought of as being the number of perceptions and corresponding actions which are necessary in order for the ANN to be able to classify a behaviour. A behaviour is found empirically to consists of 36 sequential actions (i.e. ensures the best convergence of the ANN) — which is analogue to the 36 tiles used in the experiments, and thus ensures that within the 36 steps, the child has the option to have an uniform distribution on the play area. The outputs of the ANN correspond to the eleven categories which classify the children’s behaviour as illustrated in Figure 7. The ANN is implemented as a fully-connected three layered feed-forward network using the sigmoid activation function and trained by the back-propagation method.

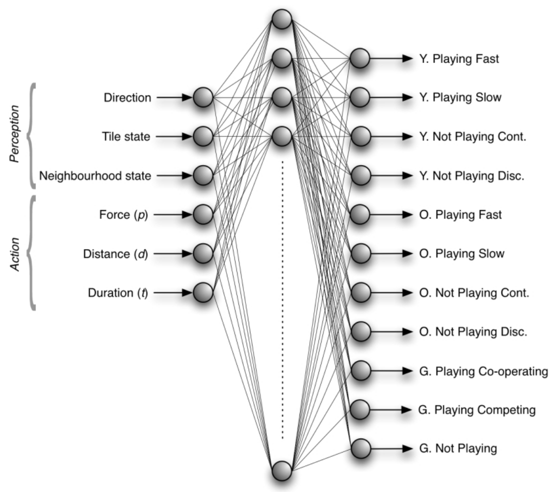

Figure 8: The architecture of the ANN design. For simplicity the history of the ANN is omitted in the figure.

The ANN was trained using a training set constructed from the observed behaviour of 7 children[2] as defining behaviours of the classes. For the defining behaviours 36 sequential actions were selected objectively by the external observer using video analysis. The configuration and convergence of the trained ANN are summarised in Table 4.

Table 4: Configuration and convergence parameter values of the trained ANN.

Parameter	Value
Number of input neurons	216
Number of hidden neurons	27
Number of output neurons	11
Learning rate, η	0.1
Training epochs	3000
Examples in training set	180
Training error, RMS	0.0034
Training error, MAX	0.020

The trained ANN was validated using a test set constructed from the collected data of the 31 remaining children from the experiments (excluding the children observed having a *None* behaviour) which were *not* used in the training process of the ANN. Before validating the ANN the subjects were categorised using an objective video analysis. The ANN classifies the validation subjects as listed in Table 5. It is apparent from Table 5 that 27 of the 29 subjects are correctly classified (93%); the misclassified cases was a child (S_{23}) categorized as "Younger Playing Fast" instead of "Older Playing Fast" and the two girls (S_{27}) which are categorized as "Group Cooperating" instead of "Group Competing".

When looking closer on the ANN output in Table 5 the classification percentage is varying. However, the output represents the overall classification of the children play during the experiment. Thus, these variations could be a result of the children changing behaviour during the experiments (see e.g. S_6). By investigating the moving average of the ANN classification for S_6 (see Figure 9) it is seen that the behaviour of S_6 is classified as either "Y. Not Playing Disc." or "Y. Not Playing Cont." during the experiment. To confirm that the changes in the ANN classifications are coherent with changes in the children's behaviour, a qualitative video analysis of the children's behaviour was made by a human classifier who classified the children's behaviour during sequences of 36 steps and assigning each classification with a confidence factor (i.e. illustrating the level of uncertainty). According to the human classifier S_6 is indeed changing her behaviour during the experiment (see Table 6). However, the behaviour changes noted by the human classifier are exactly those classified by the ANN in Figure 9 — it also appears that the confidence factor of the human classifier follows the magnitudes of the classifications by the ANN.

Table 5: ANN classification of the validation subjects. The subjects are numbered and marked as (Y)ounger/(O)lder and (M)ale/(F)emale. The ANN classification is shown as percentage of output, and bold is used to indicate the maximum output whereas underline indicates the expected classification of the subject according to the video analysis.

	Classification in percentage						
Subject(s)	Y. Playing Slow	Y. Not Playing Cont.	Y. Not Playing Disc.	O. Playing Fast	O. Playing Slow	Group Cooperating	Group Competing
$S_{1,YM}$	9	32	**55**	0	2	2	0
$S_{2,YF}$	6	10	**80**	2	2	0	0
$S_{3,YF}$	19	5	**63**	6	5	0	2
$S_{4,YF}$	1	**69**	30	0	0	0	0
$S_{5,YF}$	26	**50**	14	0	2	8	0
$S_{6,YF}$	1	**50**	41	0	5	0	3
$S_{7,YM}$	**42**	8	34	8	2	3	3
$S_{8,YF}$	12	25	**62**	0	1	0	0
$S_{9,YM}$	**55**	8	29	0	5	3	0
$S_{10,YM}$	**43**	14	39	2	0	1	1
$S_{11,YM}$	**72**	1	18	2	6	0	1
$S_{12,YF}$	3	**79**	7	0	1	10	0
$S_{13,YF}$	23	7	**56**	6	3	4	1
$S_{14,YM}$	**87**	1	3	9	0	0	0
$S_{15,YM}$	**68**	2	22	1	1	5	1
$S_{16,YM}$	**74**	0	1	15	1	9	0
$S_{17,YM}$	**59**	0	9	23	1	7	1
$S_{18,YF}$	13	8	**61**	8	1	1	8
$S_{19,YM}$	**41**	19	30	0	4	6	0
$S_{20,YM}$	**80**	0	0	16	1	3	0
$S_{21,OF}$	19	15	21	**43**	0	0	2
$S_{22,OM}$	12	7	10	**32**	16	7	16
$S_{23,OM}$	**33**	3	23	8	17	9	7
$S_{24,OM}$	19	0	2	16	**31**	30	2
$S_{25,OM}$	7	1	3	**24**	20	22	23
$S_{26,YF\&F}$	14	1	1	5	3	**45**	31
$S_{27,YF\&F}$	15	1	1	10	4	**35**	34
$S_{28,YM\&M}$	10	1	2	1	1	**60**	25
$S_{29,YM\&M}$	6	3	2	10	1	**41**	37

3.3 Adapting to Children's Behaviour

The final phase of Figure 4 is the adaptation phase. This phase includes extending the Playware playground into an Ambient Playware playground by uti-

[2] A complete training set could not be constructed, as only 7 of the 11 behaviours defined from Figure 7 existed in the data collected.

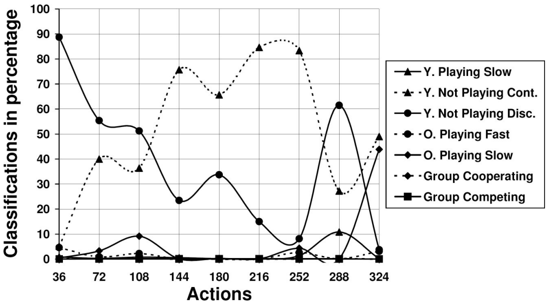

Figure 9: The moving average of the ANN classifications for the behaviour of S_6.

Table 6: Qualitative video analysis of the behaviour of S_6 by a human classifier. The confidence factors $\star$, $\star\star$ and $\star\star\star$ correspond to *vague observation*, *good observation* and *confident observation* of a behaviour respectively.

Actions	Human Classification	Confidence
0-36	Y. Not Playing Disc.	$\star\star$
37-72	Y. Not Playing Disc.	$\star\star$
73-108	Y. Not Playing Disc.	$\star$
109-144	Y. Not Playing Cont.	$\star\star$
145-180	Y. Not Playing Cont.	$\star\star\star$
181-216	Y. Not Playing Cont.	$\star\star\star$
217-252	Y. Not Playing Cont.	$\star\star$
253-288	Y. Not Playing Disc.	$\star\star$
289-324	Y. Not Playing Cont.	$\star$

lizing the classification capabilities of the ANN. By embedding the ANN into to playground, real-time adaptation of the environment according to the child's and/or children's behaviour can be realized. To do so, the implemented "Bug Smasher" game has been extending to include several adaptation strategies which adapts characteristics of the environment in order to encourage physical activity amongst the children. E.g. if a child is classified as "O. Playing Fast" the speed of the bugs is increased as is the distance to the child. Next, if the child slows down and gets classified as "O. Playing Slow" the bugs speed and distance to the child is decreased.

Preliminary experiments have showed, that the implemented adaptation strategies indeed encourages the children to a higher level of physical activity while still maintaining the interest in the playground — in some cases the interest even increased (Derakhshan et al. (2006a)).

4 Conclusions & Discussion

In this paper the novel Playware playground has been introduced and it has been shown how the playground can be adapted according to the behaviour of the children by the use of modern AI. The playground and the children playing on it have been modelled as a multi-agent system; modelling children as agents and the playground as the environment which allows for children–playground (agent–environment) and children–children (agent–agent) interactions and for the children as being organised. Having the MAS defined, an ANN has been trained using data recorded directly from the agent–environment interactions which allows for classifying the children's behaviour within eleven categories by 93%. The ANN has been embedded into the playground allowing for real-time adaptation with regards to the behaviour of the child playing. Adaptation strategies has been implemented *ad hoc* which allows for the playground to adapt in order to maintain and/or increase the child's interest.

Considering the importance and the significant increase of obesity related problems still little interdisciplinary work exists which encourage physical activity following the Playware approach by introducing technologies known from robotics, artificial intelligence and multimedia into play equipment.

However, the KidsRoom (Bobick (1996)) developed at MIT Media Laboratory offers a perceptually-based, multi-person, fully automated, interactive, narrative play space where children are taken on a fantasy journey through different worlds. Using a $24ft. \times 18ft.$ environment modelled as child's bedroom, the KidsRoom can track and analyse the behaviour of the children playing within the environment. Using sound, images, animations and music, the room can communicate with the children allowing the child (or children) to become a part of the story narrators, enabling them to change the course of the journey according to his/her behaviour and interaction with the room. Thus, the KidsRoom, like the Playware playground, allows for a high degree of freedom for child. The child does not have to know about the room's capabilities, i.e. he or she does not have to push certain buttons or do anything extraordinary for the storyline to proceed. However, the KidsRoom analyses the children's behaviour using computer vision constrained to certain fixed areas of the room, i.e. the child, in contradiction to the Playware playground, can only interact with the storyline at pre-defined areas in the room.

Also exergaming products such a *QMotions* and Konami's *Dance Dance Revolution* series of games are relating examples of entertainment media that mix physical activity with computer game playing. However, Playware offers the concept of building block game development which provides a much higher degree of freedom and flexibility in game designing. Thus, exergaming products can be considered as a sub-genre of Playware.

5 Current & Future Work

Currently work is in progress in two directions. First new experiments have been conducted to stress the effect of the adaptation on the children.

Experiments have been made where children are allowed to play the "Bug Smasher" game with and without the adaptation mechanism while measuring different entities such as response time on the playground, the number of interactions with the playground, the child's heart rate during play etc. to manifest the correlation between these different entities and adaptation. Preliminary results are indicating that the adaptation has the desired effect on increasing the physical activity of the children while playing.

Secondly new experiments are being made with a different type of game to settle the generality of the described approach taken in this paper.

In the future development of Playware playgrounds, emphasis should be placed on flexible user-centric Playware with enhanced ambient intelligence features which allows for further personalizability, adaptation and anticipatation according to the user's behaviour. This would indeed give the children and youth an exciting alternative to today's computer games and traditional physical playgrounds.

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