

Deciding Like Humans Do

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Abstract

With the objective of building robots that accompany humans in daily life, it might be favourable that such robots act humanlike so that humans are able to predict their behaviour without effort. Decision making is one crucial aspect of daily life. As Damasio demonstrated, human decisions are often based on emotions. Earlier work thus developed a decision making framework for artificial intelligent systems based on Damasio's Somatic Marker Hypothesis and revealed that overall, the decisions made by an artificial agent resemble those of human players. This paper enhances this work in so far that a detailed evaluation of the first 30 decisions made by the modelled agent during this gambling task was done by human subjects. Therefore 26 human participants were recruited who had to evaluate different graphical outputs that visualized the course of the Iowa Gambling Task played by either a modelled agent or a human. The results revealed that participants tend to categorize the course of the game as human, even if it was from the modelled agent. Furthermore, the evaluation of the different courses showed that participants were not able to differentiate between modelled and human output, but they were able to differentiate these from random courses of the game.

Introduction

Since robots are assumed to enter our daily life in the (near) future one major question is the way they should act. It can be discussed whether a humanlike behaviour is the desired goal for every application. In terms of e.g. cleaning robots a pre-wired behaviour may be sufficient, as the field of application is clearly defined. With regard to robot companions, the applications are numerous and the different behaviours a robot should perform are manifold. In addition, the desired behaviour may depend on the owner or the social environment. A study concerning the role, behaviour and acceptance of robot companions is presented by Dautenhahn in (Dautenhahn et al. 2005). The results show that nearly 40% of the subjects would like to have a robot companion and that some roles, such as the friend role, are less desirable ($\approx 20\%$), while other roles, like assistant, find higher acceptance ($\approx 95\%$). Most of the subjects stated that they prefer

a humanlike communication (71%) with the robot, while a humanlike behaviour is only preferred by 36%. However, even when the appreciation of humanlike behaviour is not as high as of humanlike communication it can be assumed that some human abilities exist, such as learning aptitude, which are preferable in terms of robot companions. In addition, most of the subjects have stated that the robot's behaviour should be predictable (90%) and controllable (71%), which makes the robot's decision making to an essential part to design robot companions. Based on these results it can be assumed that humanlike fast adaption of behaviour may be preferred but that in terms of predictability some human characteristics like defiance are predominantly undesired. In order to create reliable systems an increasing number of decision making approaches based on different psychological models of the human decision making process have been developed (Hoefinghoff and Pauli 2012) (Hoogendoorn et al. 2009) (Rolls 2008).

A popular theory concerning the human decision making process has been presented by Damasio (Damasio 1994), which emphasizes emotions as decisive determinants in the human decision making process. The so-called Somatic Marker Hypothesis stated that an emotional preselection of actions happens when a decision has to be made. This filtering process is based on somatic markers, which represent an emotional memory. Damasio distinguishes between emotions and feelings: while emotions are described as changes of the bodily state (e.g. increasing heart beat), feelings are defined as the perception of these changes. In addition, Damasio divided emotions into primary emotions and secondary emotions. Primary emotions are inbred (e.g. fear of huge animals) and trigger precast behaviour patterns like running away. Secondary emotions are created out of experiences and can therefore be very idiosyncratic. Somatic markers are images of emotions in the memory which can be used for decision making without awaiting a bodily response. This is what Damasio called the *as-if* loop because the decision making process proceeds as if there had been an emotion (changing in the body state). In case that there are no experiences, the so-called *body-loop* is triggered which leads to real changes in the bodily state. These changes will be memorized in the form of a somatic marker and can be used for decision making when the same stimulus is recognized again.

The current work aims to test whether the implementation of Damasio’s Somatic Marker Hypothesis (SMH) (Hoefinghoff and Pauli 2012) into an artificial agent leads to results comparable to human decisions. As the results just include a comparison of the overall results of human subjects and the artificial agent, a further evaluation that includes how humans perceive each decision made by the artificial agent, is presented here. The subjects have to categorize if the presented decisions have been made by a human or by an artificial intelligence. Therefore a testing environment was necessary to gather test data of human and modelled subjects. For evaluation purposes the Iowa Gambling Task (IGT) was chosen, which is explained in detail in the next section.

Iowa Gambling Task

The Iowa Gambling Task (IGT) has been created by Bechara (Bechara et al. 1994) to validate the SMH. In the task each subject receives an amount of \$2000 and has to choose between four decks of cards. For every card the subject gains a defined benefit but some cards also lead to a penalty. The dedicated goal is to increase the given amount as much as possible. The experiment ends after 100 choices, what is unknown to the subjects. An example configuration according to the rules can look like the following:

- *Deck A:* Every card gives a benefit of \$100 and five out of ten cards additionally have a penalty of -\$250
- *Deck B:* Every card gives a benefit of \$100 and one out of ten cards additionally has a penalty of -\$1250
- *Deck C:* Every card gives a benefit of \$50 and five out of ten cards additionally have a penalty of -\$50
- *Deck D:* Every card gives a benefit of \$50 and one out of ten cards additionally has a penalty of -\$250

With this configuration deck A and B are disadvantageous and deck C and D are advantageous. Ten drawn cards from a disadvantageous deck lead to a net loss of \$250, while ten drawn cards from an advantageous deck lead to a net gain of \$250. The difference within the advantageous and disadvantageous decks is the number of penalties. In this version of the game the placements of the penalties are equal for each subject. As the subjects are not allowed to take notes during the task, they are not able to calculate the net gains or losses from each deck. Accordingly they have to rely on an emotional decision making process, based on somatic markers, to create an estimation which decks are risky and which profitable. In the early stages of the experiment human subjects often choose from the disadvantageous decks A and B which can be explained by the immediate higher rewards but after some punishments they switch to the advantageous decks C and D (Damasio 1994).

Artificial Somatic Markers for Decision Making

In (Hoefinghoff and Pauli 2012) an algorithm for decision making was presented which is influenced by the SMH. Considering that a modelled agent should be able to learn based on rewards, the approach can be generally assigned to

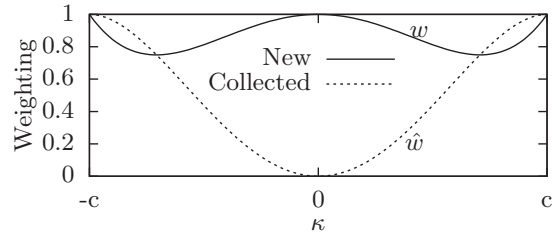


Figure 1: Weighting of new and collected knowledge in dependency of the reliability κ .

the reinforcement learning methods except that the design, computations and especially the output of the algorithm is inspired by the SMH. The algorithm uses a high abstraction level for emotions and only distinguishes between positive and negative emotions but with different degrees of intensity. This decision has been made to ensure that the algorithm can quickly be adapted to different applications and is therefore generally usable for any kind of stimulus response learning. Other approaches with a more detailed resolution of emotions may reflect the human decision making process more accurately. However, the adaption for different applications often includes the implementation of a lot of prior knowledge for every situation, such as when to trigger anger or sadness.

Basically Damasio divided the human decision making process into two main steps. The first step is a filtering process which is based on the emotional memory that is formed by the somatic markers to highlight some options. The second step consists of a further rational analysis to choose an action out of the remaining possibilities. The focus of the presented approach is on the emotional selection whose output is a set $A' \subseteq A$ that contains all remaining actions out of all actions A . It is assured that $A' \neq \emptyset$. After the emotional selection a further rational analysis could take place to choose one action a_j from the subset A' if it contains more than one element. For now a random action is chosen at this point. The framework mainly includes two parts: the modelling of somatic markers and the thereon based decision making algorithm.

Modelling of Somatic Markers

Basically a decision has to be made when a stimulus s_i occurs which calls for a reaction in form of executing an action. After the execution the outcome can be recognized which can be positive, negative or neutral. Summarized an agent with artificial intelligence mostly consists of:

1. A set $S = \{s_1, \dots, s_m\}$ which contains all stimuli that could be recognized. A stimulus can be a single signal or sensory value but also a combination of different inputs which describe a whole situation.
2. A set $A = \{a_1, \dots, a_n\}$ which contains all actions that could be executed.
3. m sets $R_{s_i} = \{r_1, \dots, r_l\}$ which contain all possible rewards that can be received for executing an action in consequence of this stimulus.

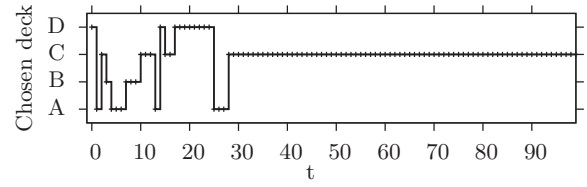
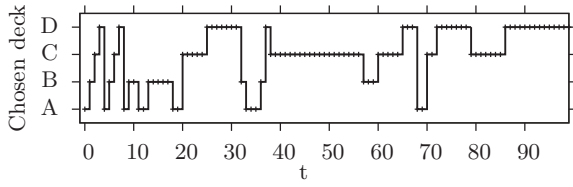


Figure 2: Decisions of a typical human subject (Bechara et al. 1994) (left) and an exemplary result of the modelled agent (right).

As a somatic marker represents the emotional memories concerning a pair of a stimulus and an action, a $(m \times n)$ matrix M (see eq. (1)) is created that contains all somatic markers.

$$M = \begin{pmatrix} M_1 \\ \vdots \\ M_m \end{pmatrix} = \begin{pmatrix} \sigma_{1,1} & \cdots & \sigma_{1,n} \\ \vdots & \ddots & \vdots \\ \sigma_{m,1} & \cdots & \sigma_{m,n} \end{pmatrix} = (\sigma_{i,j}) \quad (1)$$

After the execution of an action a_j the agent obtained a reward r_k out of the set R_{s_i} . Based on the obtained reward the corresponding somatic marker $\sigma_{i,j}$ is updated (see eq. (2),(3)), while all other somatic markers stay unaffected. The computation of a somatic marker considers new knowledge and already collected knowledge. The weighting of new knowledge (w) and collected knowledge (\hat{w}) depend on the reliability of collected knowledge. Therefore an own value κ_i is introduced for each stimulus, which represents the reliability of the collected knowledge. Figure 1 shows the weighting, in which c is a user-given constant. It can be observed that only new knowledge is considered when $\kappa_i = 0$, which means that collected knowledge is not present or not reliable. If collected knowledge is most reliable ($\kappa_i = c$ or $-c$), both new and collected knowledge is fully considered to enable a possible reversal learning process. An exclusive consideration of collected knowledge in this case would make the agent unable to adapt its behaviour because all rewards from this point will be discarded. The decreased weighting of new knowledge during the learning period counteracts the influence of single outliers in the rewards. Basically the value κ_i will be increased in the case of sequent positive rewards and decreased in the case of sequent negative rewards. The magnitude of the increasing/decreasing depends on the magnitude of the reward (Hoefinghoff and Pauli 2012).

$$\overline{r_{i,j}^t} = w \cdot r_{i,j}^t + \hat{w} \cdot \overline{r_{i,j}^{t-1}} \quad (2)$$

$$\sigma_{i,j}^{t+1} = \tanh(\overline{r_{i,j}^t}) \quad (3)$$

Decision Making Algorithm

As the decision making algorithm should be based on the somatic markers a criterion is necessary when an action is added to the selected subset. Therefore a threshold θ_i is created for each stimulus which can be interpreted as a frustration level (see equation (4)). This frustration level is used as a threshold for the selection of actions. A major difference to other comparable approaches (Hoogendoorn et al. 2009)

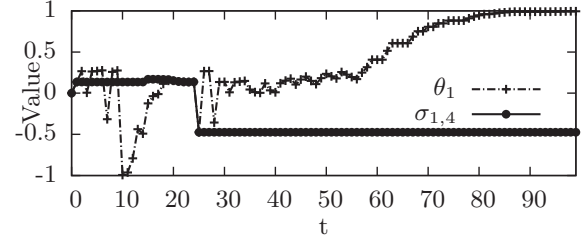


Figure 3: Values of the somatic marker for deck 4 and the corresponding threshold.

(Pimentel and Cravo 2009) is that the threshold is an automatically adapted value instead of a fixed, user-given value. Any time the agent recognized a stimulus s_i the subset A' will be selected. The definition of A' can be seen in equation (5). Based on the obtained reward the corresponding somatic marker and also the frustration level θ_i will be updated. The update of θ_i is computed with the same equation as for the somatic markers (see eq. (2), (3)), but there is a difference in the number of updates. While the frustration level will always be updated when a stimulus is recognized, the update of a somatic marker depends on a combination of both a stimulus and an action. Figure 2 shows an example for the decisions of a typical human subject (Bechara et al. 1994) and the modelled agent. The corresponding progress of the somatic marker for deck D and the threshold of the exemplary run is shown in figure 3. It can be observed that the somatic marker value $\sigma_{1,4}$ only changes when the action is chosen, while the threshold θ_i changes after every decision. In the case that no somatic marker fulfils the condition (5) further mechanisms are described in (Hoefinghoff and Pauli 2012) to assure that $A' \neq \emptyset$.

$$\vec{\theta} = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_m \end{pmatrix}, \quad \theta_i \in]-1; 1[\quad (4)$$

$$A' := \{a_j \in A \mid \sigma_{i,j} \geq \theta_i\} \quad (5)$$

Results of the Artificial Agent Performing the Iowa Gambling Task

Figure 4 shows the results of the artificial agent ($N=100$), performing the gambling task, that have been presented in (Hoefinghoff and Pauli 2012). The results of the simulated artificial agent compared to human subjects performing the gambling task show similarities in an overall high preference of the advantageous decks C and D. It is observable that the

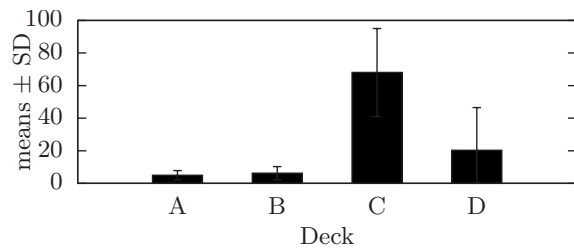


Figure 4: Results of the artificial agent performing the gambling task (N=100).

proportion of choices from deck C is nearly 70%, which results from the fact that the corresponding somatic marker could not have a negative value because of the possible rewards (0 or +50). In the case that all other somatic marker values become negative, it is very likely that only deck C will be chosen. In early phases of the experiments human subjects often choose from the disadvantageous decks A and B, which could be explained with the potentially higher reward. An early preference for disadvantageous decks is also reflected in the results of the modelled agent. The results of a repetition of the experiment show that the proportion of choices from disadvantageous decks is $\approx 35\%$ when only the first 30 choices are considered, whereas the overall proportion (100 choices) is low ($\approx 10\%$). Although the results demonstrated that the overall behaviour of the modelled agent is comparable to human subjects, differences with respect to later choices were observable. In contrast to the modelled agent human subjects made few choices in later stages from the disadvantageous decks which may result from the fact that the human decision making process is further influenced by other factors like personal characteristics (e.g. curiosity or risk-taking). Hence it can be assumed that the current decision making framework offers a well suited adaption of the human decision making process during the early phases of the experiment. Therefore a more elaborate study was conducted to identify similarities and differences perceived by humans between the choices of human players and the modelled agent.

Evaluation Study

With the objective of testing whether humans are able to distinguish the decisions made by the modelled agent from those of human players in the early stages of the IGT, a study was conducted in which each subject had to evaluate 12 different courses of the IGT which stem from human or artificial players. As the focus lies on a further evaluation of the decision making approach, several graphical outputs, which reflect the choices made by human and modelled players during the IGT, were produced to make sure that the kind of robot does not affect the results. These graphical outputs have to be evaluated by human participants with regard to predictability and naturalness.

Participants

In total 26 persons (15 male) between 20 and 49 years (MEAN = 25.5; SD = 5.16) volunteered in the present study

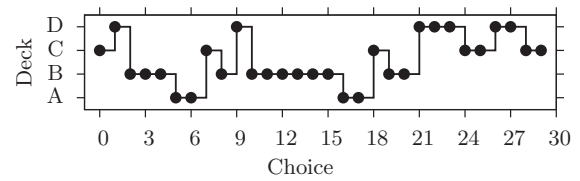


Figure 5: Example for the visualization of the first 30 choices.

whereof 5 were recruited to endorse the results with think aloud protocols. The majority of the participants (18) did not know the IGT before. The influence of this variable was controlled but did not affect the variables of interest.

Stimulus Material

First of all, participants had to be enabled to observe the decisions made during the test runs. Therefore a graphical visualization was chosen that reflects each decision made during the first 30 stages of the IGT. For this purpose data that was gathered of human (N=30) and modelled players (N=100) was transferred into graphical output files (figure 5). Out of the obtained material 10 different outputs were randomly selected, 5 from human players and 5 from the modelled agent. Additionally, two randomly generated outputs were included to ensure that participants are able to differentiate between differences in output files at all. In total 12 graphical output files were selected.

Measurements

To test if the artificial somatic marker framework leads to comprehensible decisions from human views, output graphics of random, human and artificial players were presented to the participants which had to be rated by means of 8 item-pairs on a 5-point semantic differential (1). These items were chosen to measure how comprehensible and predictable the decisions of the player were perceived and how natural the course of the game was evaluated.

Furthermore, the participants' criteria for the evaluation of the output files were of great interest. Here, participants should indicate whether they used one or more of 6 given criteria, namely: 1) the frequency of changing decks, 2) similarity to own procedure, 3) procedure at the beginning, 4) procedure at the end, 5) comprehensibility, and 6) tendency to choose good decks.

Additionally, age, gender, education, and prior experience with the IGT were collected as moderating aspects that might have affected the evaluation.

General Procedure

Initially, each participant was instructed to solve the IGT at a computer. In contrast to the studies of Damasio (Bechara et al. 1994) a version of the IGT that includes randomly generated decks has been used since it has been criticised in (Fellows and Farah 2005) and (Kovalchik and Allman 2006) that the placement of the punishments might have influenced the results. When the participant finished the task the experimenter explained the configuration of the decks (e.g. A and B are disadvantageous decks as they lead to a loss of money

| | Factor | |
|-----------------------------------|----------------|-------------|
| | predictability | naturalness |
| comprehensible - incomprehensible | .773 | |
| predictable - unpredictable | .732 | |
| random - deliberate | -.674 | |
| familiar - unfamiliar | .658 | |
| complex - simple | -.658 | |
| human - machine-like | | .882 |
| artificial - natural | | -.836 |
| programmed - spontaneous | | -.728 |
| cronbach's alpha | .749 | .773 |
| explained variance (%) | 34.46 | 27.95 |

Table 1: Factor analysis for the evaluation of the output graphics.

when drawing more than 10 cards). Given that it could be expected that participants might have difficulties to evaluate the graphical outputs of other players, an output file which visualized the participant's own 30 decisions during the IGT was instantly generated by the experimenter. Then the participants had to explain their choices based on the output file.

For the main part of the study an online survey was displayed on the screen which included the graphical outputs (in random order) as well as items to evaluate the stimulus material. Participants were told that the graphics stem from either a human player or a computer. Each page of the survey showed one graphical output file followed by the evaluation items. For each graphical output participants were instructed to try to reconstruct the course of the IGT while observing it. Afterwards, they were told to rate the course of the game according to the bipolar items listed in table 1 and indicate whether they believed that the player was human or artificial. After participants passed this procedure twelve times, they were asked on which criteria they based their decisions. Ultimately, moderating aspects were collected before participants were fully debriefed and thanked for participation.

Results

For the purpose of comparing the different types of outputs (modelled, human, random), the dependent variables were summarized into one variable for each type output (i.e. the evaluations of agent1 - agent5 were summarized in the variable evaluation of agent output).

Evaluation of the Course of the Game

The bipolar item-pairs for the evaluation of the output graphics were reduced via factor analysis. Two factors could be extracted which were labelled predictability (5 items, cronbach's $\alpha = .749$) and naturalness (3 items, cronbach's $\alpha = .773$) according to their constituting items (see table 1). These factors were used for further analysis.

To test whether the output files of the modelled agent could be distinguished from those produced by humans or random assignment, repeated-measures ANOVAs were conducted for predictability and naturalness as dependent variables and type of the output (modelled, human or random) as within-subject variable, contrasting each type with the

| | categorized as computer | categorized as human | total |
|----------|-------------------------|----------------------|-------|
| modelled | 42 | 63 | 105 |
| human | 40 | 65 | 105 |
| random | 15 | 27 | 42 |

Table 2: Frequencies for the categorization of each output (N=21).

modelled agent. The analysis yielded a significant main effect for predictability ($F(2; 20)=55.05$; $p < .001$; $\eta=.734$). According to innersubject contrasts, the evaluation of the modelled agent differed significantly ($p < .001$) from randomly assigned outputs, but not ($p .05$) from human ones. Outputs from the modelled agent ($MEAN=-0.20$, $SD=0.47$) and human outputs ($MEAN=-0.13$, $SD=0.25$) were (surprisingly) perceived as less comprehensible and familiar than randomly assigned ones ($MEAN=0.96$, $SD=0.63$). It can be concluded that the framework is able to produce decisions that are comparable to human decisions, at least with respect to predictability.

With respect to naturalness no main effect was obtained. Also the moderating variables had no significant impact on the results when they were included as covariates.

Categorization as Human or Computer

Besides the evaluation of the factors predictability and naturalness, the participants' choice whether the player was a human or a computer was analysed with regard to the different output types. As depicted in table 2 all types of output files were more frequently categorized as made by a human player than by a computer. χ^2 -tests for each output type revealed that these differences were significant for the outputs of the modelled agent ($\chi^2(1, N=21)=4.20$, $p=.05$) and the human player ($\chi^2(1, N=21)=5.95$, $p=.019$). Random outputs were not significantly more often categorized as 'human' or 'computer'. While random output files lead to confusion and uncertainty on the side of the participant resulting in arbitrary choices of human or computer, the other outputs (modelled and human) were significantly more often identified as humanlike.

Evaluation Criteria

In order to answer the question why the output files were perceived as humanlike, or which criteria served as basis for the evaluation, different criteria were also checked within the analyses. The criteria were mainly collected to give further insights based on which criteria outputs from human and artificial players were distinguished, if they can be distinguished at all. The results of the main study revealed that no difference between the outputs from the modelled agent and human players were observable. Thus, it was no longer necessary to take a closer look at the criteria in order to analyse which one is the decisive criterion that distinguishes the modelled output from human output files. Consequently, the results gained for the criteria are only briefly summarized in the following.

This finding is also resembled in the participants' choices of the given criteria and further mentioned criteria (from the

| criteria | frequency of choice |
|-------------------------------|---------------------|
| frequency of changing decks | 18 |
| similarity to own procedure | 16 |
| procedure at the beginning | 14 |
| comprehensibility | 14 |
| tendency to choose good decks | 14 |
| procedure at the end | 9 |

Table 3: Frequencies of choosing the given criteria (N=26).

survey and the protocols). Almost all given criteria are chosen equally often, demonstrating that no single one seems to be the one criterion that determines whether the output is perceived humanlike or artificial (see table 3). Instead, all criteria seem to be equally important for the evaluation of the output files, and are moreover equally fulfilled by the modelled and the human outputs.

However, the analysis of the think aloud protocols revealed that the criteria given in the questionnaire were relevant to the evaluation of the IGT since the same criteria could be extracted from the protocols. Further, participants reported (in the survey as well as in the think aloud sessions) that they also considered many other criteria for their evaluation like testing of each deck in the beginning, repetition of procedures or often one deck was chosen consecutively.

Furthermore, the think aloud protocols exemplified that the descriptions (criteria) participants used to explain the outputs did not allow any general conclusion whether the output is humanlike or not. As the results showed, the outputs from the modelled agent as from humans resemble what the participants perceived as human(-like) decision making.

Discussion

The major aim of the current paper was to test if the decision making framework based on artificial somatic markers provides a good adaption to the human decision making process. Therefore a study was conducted, in which human subjects had to rate the choices of an unknown player and decide if the decisions were made by a human player or a computer. The results demonstrate that the human subjects were not able to distinguish between the output files of human players or the artificial agent. Furthermore, information about the criteria that were used by the subjects for the categorization were collected. The evaluation of the criteria revealed that no criterion was chosen exceptionally often. Hence, it can be assumed that no single criterion is applied for the categorization and no general evaluation pattern exists among humans. As the main study revealed that there was no significant difference between the outputs from the modelled agent and human players, both decision making processes must have fulfilled the criteria.

While the outputs of humans and the modelled agent were categorized as humanlike more often, the classification of random outputs was arbitrary. Although the random outputs were surprisingly perceived as more predictable, it can be supposed that this effect might have resulted from an uncertainty while rating the randomly generated outputs that did not match the assessment criteria. Certainly it could not

be ensured that the complexity of the evaluation task itself might have influenced the results. Furthermore the amount of output graphics (12) presented to one subject might have been too much resulting in a fatigue effect. However, the stimulus material was presented in random order to control this bias.

Since the results of Hoefinghoff (Hoefinghoff and Pauli 2012) already demonstrated that differences between the decision making of human subjects and the artificial agent were observable in later choices of the IGT, the present study focussed on the first 30 choices. It remains open to investigate whether the output of human players is distinguishable from the output of the artificial agent when the whole 100 choices are presented. The results of such a study could be useful to extract information to enhance the framework in order to reach a more humanlike approximation for the whole task. Furthermore, subsequent work should include the evaluation of the decision making framework in different applications like reversal learning tasks to test the generalization aspects. With regard to implementing this humanlike decision making behaviour into robots that accompany humans in daily life it is necessary to evaluate the impact of the kind of decision making on likeability and sympathy of robots (or other artificial entities). The evaluation of these aspects would help to identify to what extent a humanlike behaviour is perceived as the desired behaviour of an artificial intelligence system and how great the impact of the given application would be.

References

- Bechara, A.; Damasio, A.; Damasio, H.; and Anderson, S. 1994. Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition* 50:7–15.
- Damasio, A. 1994. *Descartes Error: Emotion, Reason, and the Human Brain*. Putnam Press.
- Dautenhahn, K.; Woods, S.; Kaouri, C.; Walters, M. L.; Koay, K. L.; and Werry, I. 2005. What is a robot companion - friend, assistant or butler. In *In Proc. IEEE IROS*, 1488–1493.
- Fellows, L. K., and Farah, M. J. 2005. Different underlying impairments in decision-making following ventromedial and dorsolateral frontal lobe damage in humans. *Cerebral Cortex* 58–63.
- Hoefinghoff, J., and Pauli, J. 2012. Decision making based on somatic markers. In *Proceedings of the Twenty-Fifth International Florida Artificial Intelligence Research Society Conference*, 163–168. AAAI Press.
- Hoogendoorn, M.; Merk, R.; Roessingh, J.; and Treur, J. 2009. Modelling a fighter pilot's intuition in decision making on the basis of damasio's somatic marker hypothesis. In *Proc. of the 17th Congress of the Int. Ergonomics Association*. CD-Rom.
- Kovalchik, S., and Allman, J. 2006. Measuring reversal learning: Introducing the variable iowa gambling task in a study of young and old normals. *Cognition and Emotion* 20:714–728.
- Pimentel, C., and Cravo, M. 2009. Don't think too much! - Artificial somatic markers for action selection. In *Int. Conf. on Affective Computing and Intelligent Interaction*, volume 1, 55–62. Amsterdam: IEEE.
- Rolls, E. 2008. *Memory, Attention, and Decision-Making: a unifying computational neuroscience Approach*. Oxford University Press.