

Decision Making Based on Somatic Markers

Jens Hoefinghoff and Josef Pauli

Fakultaet fuer Ingenieurwissenschaften, Universitaet Duisburg-Essen
47057, Duisburg
jens.hoefinghoff@uni-due.de; josef.pauli@uni-due.de

Abstract

Human decision making is a complex process. In the field of Artificial Intelligence, decision making is considered an essential aspect of autonomous agents. Research of human decision behaviour shows that emotions play a decisive role. We present a computational model for creating an emotional memory and an algorithm for decision making based on the collected information in the memory. We concentrate on simulating human behaviour as there is not always one perfect way to reach a goal but alternatives that are more advantageous. For evaluation purposes a gambling task, performed by real subjects, was created for the modelled agent. The results show that the decision behaviour of the modelled agent is comparable with real subjects.

Introduction

Our lives are affected by decisions. Due to the complexity of the factors that lead to a decision human decision making processes are still a relevant field of research. One popular theory concerning decision making was proposed by Damasio. In his so called *Somatic Marker Hypothesis* he describes the significance of emotions in the decision making process (Damasio 1994). The function of emotions is specified as a filtering process to select a subset of actions before a rational analysis is executed. Principal components of Damasio's theory are the *Somatic Markers* that are representing images of certain emotions for each pair of stimulus and action. By creating *Somatic Markers* it is possible to build up an emotional memory. Those recorded images of emotions can be used for decision making without waiting for a response of the body. That is what Damasio called the *as if loop* because the further processes will be triggered as if there was a real emotion. As robots take more and more part in the society (Dautenhahn 2002), it is necessary to create agents which are able to find acceptance and react as humanely as possible. In the following chapters we present a computational model for *Somatic Markers* and a thereon based decision making algorithm in which no fixed threshold is used. The performance of the presented approach was evaluated with a simulated agent that had to perform the same task as real

subjects in an experiment created by Bechara (Bechara et al. 1994).

Related Work

Emotion modelling for the decision making process of artificial agents is used in several approaches, some of which are using emotions in addition to common learning methods. But there also exist frameworks in which the learning of behaviour only depends on emotion modelling approaches. A framework in which Somatic Markers are used for decision making can be found in (Pimentel and Cravo 2009), a further approach is presented in (Hoogendoorn et al. 2009). Both use different implementations for Somatic Markers and for decision making algorithms and a fixed user-given threshold for action selection. When applying such approaches to a real robot intended to be embedded in a social environment, the thresholds for different stimuli may have to be varied. These individual thresholds are hard to model as the rewards may not be predictable and a lot of knowledge is necessary. Therefore a new framework, including an automatically adaptive threshold is presented here.

Modelling of Somatic Markers

Basic Components of the Agent

An agent with artificial intelligence mostly consists of the following components:

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. Just like in real life, some decisions are riskier than others, e.g. the gravity of the worst case scenario is depending on the existing stimulus. Therefore an own set of rewards for every stimulus is necessary.

Definition and Role of Somatic Markers

Every time the agent recognizes a known stimulus s_i , a decision has to be made. The chosen action a_j will lead to a

reward r_k out of the set R_{s_i} . A negative reward will lead to a negative emotion and a positive reward will lead to a positive emotion. The task of *Somatic Markers* is to record emotions which represent the made experiences for choosing an action a_j if a stimulus s_i is recognized. According to that for each pair of stimulus s_i and action a_j a value $\sigma_{i,j}$ exists which represents the *Somatic Marker* (1).

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

Normally the agent should not have any knowledge in the beginning. This will be realized by initializing the whole matrix with zeros. The computation of the *Somatic Markers* is based on the received rewards. The human emotional memory can be continuously updated every time it is getting new information in the form of a reward, which is the consequence of a made decision concerning a specific stimulus. To model this updating process, collected knowledge ($\overline{r_{i,j}^{t-1}}$), new knowledge ($r_{i,j}^t$) and a weighting between them should be considered. For this reason an exponential smoothing (Winters 1960) (see equation (2)) is used for the incoming rewards because it fulfils the combined request.

$$\overline{r_{i,j}^t} = \lambda \cdot r_{i,j}^t + (1-\lambda) \cdot \overline{r_{i,j}^{t-1}}, \quad r_{i,j}^t \in R_{s_i}, \quad \lambda \in [0, 1] \quad (2)$$

The smoothed value is used as input for a tanh function which maps it to the interval $]-1; +1[$, where a negative value indicates a negative emotion and a positive value indicates a positive emotion. There are also two additional characteristics of the tanh that are interesting. First, the high gradient for inputs near to zero, which allows the agent to perform an explicit categorization in order to determine if a decision was good or bad even after a few decisions. Second, the decreasing gradient for higher or lower inputs which ensures that consolidated knowledge is resistant to fluctuation. At this point the computation for a *Somatic Marker* is shown in equation (3). It is observable that the value $\overline{r_{i,j}^{t-1}}$ is needed for the computation. Instead of saving this value, it is possible to compute it by using equation (4).

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

$$\overline{r_{i,j}^{t-1}} = \tanh^{-1}(\sigma_{i,j}^t) \quad (4)$$

Scaling of Rewards

A problem which needs to be fixed is the scaling of the rewards. As the computation range on computers is limited, which can lead to wrong outputs of the tanh, the scaling shown in equation (5) is used. The reason for selecting π is that the result of $\tanh(\pi)$ is close to 1 and the computation range is sufficient. In the following the symbol r_{scaled}^t for scaled rewards will be abandoned and it will be assumed that every reward r^t is already scaled.

$$r_{scaled}^t = \frac{r^t}{\max \{|r| \mid r \in R_{s_i}\}} \cdot \pi \quad (5)$$

Consideration of Frequency

It is not guaranteed that the worst reward and the best reward share the same absolute value. Due to the fact that an exponential smoothing and a scaling is used, some *Somatic Markers* do not converge against $\tanh(\pi)$ or $\tanh(-\pi)$ but against another level. For example if $\min(R_{s_i}) < 0$, $\max(R_{s_i}) > 0$ and $|\min(R_{s_i})| \gg |\max(R_{s_i})|$ is the case. Here no *Somatic Marker* could converge against $\tanh(\pi)$ even when only positive rewards are given. Also it should be considered that frequently given rewards with a lower magnitude can reach the same impact on decision behaviour than a single reward with a higher magnitude. To reach these goals the exponential smoothing needs to be modified. Table 1 shows the desired weighting of knowledge in different situations. In the case that collected knowledge is unreliable only new knowledge should be considered. But instead of considering only collected knowledge if it is reliable, both, collected and new knowledge, will be fully considered. The reason is that new knowledge will probably match with collected knowledge, which means if collected knowledge e.g. is positive the probability is high that the same action will lead to a positive outcome. During the learning period a weighting shown in table 1 is used. With this new weighting it can be shown that every *Somatic Marker* can converge against $\tanh(\pi)$ or $\tanh(-\pi)$ even for frequently given rewards with a lower magnitude. An other advantage is that the agent is still able to perform a reversal learning process if necessary because if e.g. collected knowledge is positive but the agent gets a high punishment this has a major influence on the *Somatic Marker*, in case of a minor punishment the influence is small so that the *Somatic Marker* will not change a lot. During the learning period collected knowledge and new knowledge should have an effect on the computation of *Somatic Markers*. Considering the described goals in Table 1 the modification of equation (2) can be seen in equation (6) where the parameters λ and μ will be computed with the quadratic functions (7) and (8).

$$\overline{r_{i,j}^t} = \underbrace{(\mu + \lambda - (\lambda \cdot \mu))}_{\text{weighting new knowledge}} \cdot r_{i,j}^t + \underbrace{((1-\lambda) + (\lambda \cdot \mu))}_{\text{weighting collected knowledge}} \cdot \overline{r_{i,j}^{t-1}} \quad (6)$$

$$\lambda = \frac{1}{-(c^2)} \cdot (\kappa)^2 + 1 \quad (7)$$

$$\mu = \frac{1}{c^2} \cdot (\kappa)^2 \quad (8)$$

The parameter κ represents how reliable the collected knowledge is rated, while c is a constant that defines the limits when collected knowledge is most reliable. A visualisation of the weighting functions can be seen in figure 1. When κ is 0 the agents collected knowledge is not reliable or no knowledge available, if κ is reaching c or $-c$ collected knowledge is most reliable. It is observable that collected knowledge is taken more into account when it becomes more reliable. New knowledge will always be considered so that the agent is always able to change its behaviour, the decreasing of the weighting during the learning period avoids that

the *Somatic Marker* is affected too much by a single outlier. Notice that the output of (6) could be outside of the interval $[-\pi; +\pi]$, hence the result is set to π or $-\pi$ in this case.

Case	$\bar{r}_{i,j}^t$
Unreliable knowledge	$1 \cdot r_{i,j}^t + 0 \cdot \bar{r}_{i,j}^{t-1}$
Reliable knowledge	$1 \cdot r_{i,j}^t + 1 \cdot \bar{r}_{i,j}^{t-1}$
Learning period	$w \cdot r_{i,j}^t + \hat{w} \cdot \bar{r}_{i,j}^{t-1}, w + \hat{w} \in]1; 2[$

Table 1: Desired weighting after changing equation (2).

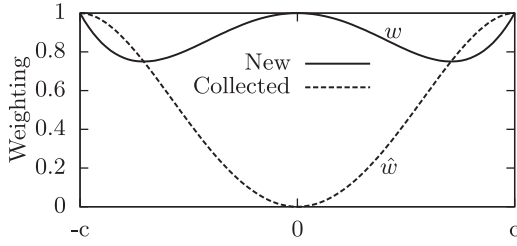


Figure 1: Weighting of new and collected knowledge

As described before, the weighting of new knowledge and collected knowledge depends on the reliability of collected knowledge which is represented by κ_i for each stimulus (9). At initialisation the value is set to zero, when e.g. getting sequent positive rewards the value κ_i^{t+1} increases in each step until it reaches the value c which means that the collected knowledge is rated as most reliable. The same holds for sequent negative rewards and reaching $-c$. The computation (see equation (10) (11)) also considers the magnitude of the current reward, so that rewards of a higher magnitude will have more influence on the computation. The rounding ensures that rewards with a small magnitude at least increase or decrease κ_i^{t+1} by 1.

$$\vec{\kappa} = \begin{pmatrix} \kappa_1 \\ \vdots \\ \kappa_m \end{pmatrix}, \quad \kappa_i \in [-c, c], \quad c \in \mathbb{N} \quad (9)$$

$$\widehat{\kappa_i^{t+1}} = \begin{cases} \kappa_i^t, & \text{if } r_i^t \vee r_i^{t-1} = 0 \\ \kappa_i^t + \left\lceil \frac{r_i^t}{\max\{|r| \mid r \in R_{s_i}\}} \cdot c \right\rceil, & \text{if } r_i^t > 0 \\ \kappa_i^t + \left\lfloor \frac{r_i^t}{\max\{|r| \mid r \in R_{s_i}\}} \cdot c \right\rfloor, & \text{if } r_i^t < 0 \end{cases} \quad (10)$$

$$\kappa_i^{t+1} = \begin{cases} -c, & \text{if } \widehat{\kappa_i^{t+1}} < -c \\ c, & \text{if } \widehat{\kappa_i^{t+1}} > c \\ \widehat{\kappa_i^{t+1}}, & \text{else} \end{cases} \quad (11)$$

Selecting Actions

Desired Output

For creating an algorithm to make decisions based on *Somatic Markers*, the desired output of such an algorithm has to be defined. The main task of *Somatic Markers* are postulated by Damasio as follows:

Somatic markers do not deliberate for us. They assist the deliberation by highlighting some options (either dangerous or favorable), and eliminating them rapidly from subsequent consideration. (Damasio 1994)

Given this statement for the output of the algorithm, the desired output has to be a set $A' \subseteq A$ which contains all actions that are still available. Afterwards a further cost/benefit analysis between the available actions could be made, but in the following there will be no further analysis and the agent randomly chooses an action out of A' .

Threshold

The set A' includes all actions a_j whose corresponding value $\sigma_{i,j}$ is greater or equal to a threshold. In contrast to the work of (Pimentel and Cravo 2009; Hoogendoorn et al. 2009) which also modelled a decision making algorithm based on *Somatic Markers*, no fixed user-given threshold is used. Here an own threshold θ_i (12) exists for every stimulus. The threshold can be seen as a frustration level of the agent. If the agent is getting punished for a decision regarding a special stimulus the corresponding threshold will decrease which may let the agent consider other options next time, while the decision behaviour for other stimuli remains unaffected. The frustration level also depends on rewards and the same equations as are used for updating the *Somatic Markers* are used, but there is a difference in the number of updates. While the frustration level will always be updated when a stimulus is recognized (13), the update of a *Somatic Marker* is depending on a combination of both a stimulus and an action.

$$\vec{\theta} = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_m \end{pmatrix}, \quad \theta_i \in]-1; 1[\quad (12)$$

$$\theta_i^{t+1} = \tanh(\bar{r}_i^t) \quad (13)$$

Selection Conditions

The current selection condition can be expressed like in equation (14). It is possible that the selection leads to an empty set A' as no *Somatic Marker* fulfils the condition. To solve the problem of the empty set, two additional cases need to be considered to ensure that $A' \neq \emptyset$.

$$a_j \in A' \Leftrightarrow \sigma_{i,j} \geq \theta_i \quad (14)$$

1. For the first case (15), the solution is expressed in equation (16). Because all values lie within the interval $[0; 1[$, the newly created threshold by using the multiplication (see (16)) is smaller than the maximum of all *Somatic Markers* and it is also possible that *Somatic Markers*

which are close to the maximum lie above the new threshold, too. Observe that the value θ_i will not be changed and will be used in the next steps.

$$\theta_i \geq 0 \wedge \max(M_i) \geq 0 \wedge \theta_i > \max(M_i) \quad (15)$$

$$a_j \in A' \Leftrightarrow \sigma_{i,j} \geq \theta_i \cdot \max(M_i) \quad (16)$$

2. For the second case (17), actions should become available which are marked as bad choices but whose *Somatic Marker* has got a higher value than the worst one. When using the condition shown in (18) the setting of the threshold depends on the difference between the maximum and the minimum of *Somatic Markers*. If there is a small difference, for example 0, the threshold will be -1 and all actions become available because their *Somatic Markers* lie within the interval $]0; -1[$ and so they are greater than the new threshold. This is the desired output because no alternative is better than another one. In case of a high difference the threshold will be close to the maximum and only the maximum or values close to it will be greater than the threshold.

$$\max(M_i) < 0 \wedge \theta_i > \max(M_i) \quad (17)$$

$$a_j \in A' \Leftrightarrow \sigma_{i,j} \geq -\left(\frac{\max(M_i)}{\min(M_i)}\right) \quad (18)$$

Algorithm

After introducing all parts and equations, the decision making algorithm can be combined to the following steps:

1. Recognition of a stimulus s_i
2. Selection of subset A' respective to s_i (14),(16),(18)
3. Random choice of action a_j from A'
4. Reception of reward r^t for the executed action a_j
5. Update of the corresponding *Somatic Marker* $\sigma_{i,j}$ (3)
6. Update of the frustration level θ_i (13)
7. Update κ_i (10), (11)

Evaluation

Gambling Task

To support the *Somatic Marker Hypothesis*, Bechara developed the so called *Gambling Task* (Bechara et al. 1994; Damasio 1994). In this experiment a subject is given 2000\$ (play money, but looking like real money) and sits in front of four decks of cards. The subject can take a card from an arbitrary deck and it is not allowed to take notes. Each card gains a benefit but some cards also lead to a penalty. This procedure will be repeated 100 times and after every turn the given amount will be updated. The number of trials is not known by the subjects. The goal is to increase the given amount. Every deck is prepared in a special way:

- *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\$

After ten cards from *deck A* the subject has a net loss of 250\$. The same goes for taking cards from *deck B* but with the difference that *deck A* contains more frequent penalties with a lower magnitude and *deck B* contains less frequent penalties with a high magnitude. As the net loss of both is negative they could be declared as disadvantageous decks. In contrast *deck C, D* have a net of 250\$ and can be declared as advantageous decks. The results show that people who have no damage in regions of the brain which are responsible for creating *Somatic Markers*, avoid the disadvantageous decks and choose more often from the advantageous decks. A control group with ventromedial frontal patients show a preference for cards of the disadvantageous decks. The dedicated goal of this approach is to reach comparable results to healthy people, so the same task is prepared for the simulated agent.

Initialisation

Taking the *Gambling Task* as a basis, the system of the agent contains the following components:

- $S = \underbrace{\{takeCard\}}_{s_1}$
- $A = \underbrace{\{deckA\}}_{a_1}, \underbrace{\{deckB\}}_{a_2}, \underbrace{\{deckC\}}_{a_3}, \underbrace{\{deckD\}}_{a_4}$
- $R_{s_1} = \{-1150, -200, -150, 0, 50, 100\}$

There is only one stimulus *takeCard* and four different possible actions which stand for taking a card from a deck. With the explained configuration of the decks six different rewards are possible. Remember that even when there is a penalty the subject also earns money. For example by taking a card from deck B that lead to a penalty the total reward is $100 - 1250 = -1150$. The evaluation consists of 100 runs where in each run the agent has to make 100 decisions so totally 10000 decisions are considered. All data will be reset after each run. At the beginning of each run every action will be executed once before the selection process becomes active. For the parameter c the value 10 is used. So a positive reward of 50 will increase κ by one while a reward of -1150 will decrease κ by ten. A very small value like 1 for c is not advisable because collected knowledge is too fast declared as reliable or will be discarded too fast. A higher value (e.g. 100) has the effect that more frequent lower magnitude rewards are needed to reach the same weighting as the maximum magnitude (because of the rounding). The overall results here are not extremely sensitive concerning a higher value for c but some decisions are not as desired.

t	θ_1	$\sigma_{1,1}$	$\sigma_{1,2}$	$\sigma_{1,3}$	$\sigma_{1,4}$	A'	a_j	r^t	r_i^{t-1}	κ_1
0	0.00	0.00	0.00	0.00	0.00	$\{a_1, a_2, a_3, a_4\}$	a_4	-200	0	0
1	-0.49	0.00	0.00	0.00	-0.49	$\{a_1, a_2, a_3\}$	a_1	-150	-200	0
2	-0.38	-0.38	0.00	0.00	-0.49	$\{a_2, a_3\}$	a_3	0	-150	-2
3	-0.03	-0.38	0.00	0.00	-0.49	$\{a_2\}$	a_2	100	0	-2
4	0.25	-0.38	0.25	0.00	-0.49	$\{a_2\}$	a_2	100	100	-2
...
18	0.26	-0.38	0.26	0.00	-0.49	$\{a_2\}$	a_2	-1150	100	1
19	-0.99	-0.38	-0.99	0.00	-0.49	$\{a_1, a_2, a_3, a_4\}$	a_1	-150	-1150	-9
...
44	0.13	-0.39	-0.99	0.13	0.14	$\{a_3, a_4\}$	a_4	-200	50	0
45	-0.49	-0.39	-0.99	0.13	-0.49	$\{a_1, a_3, a_4\}$	a_4	50	-200	-2
46	0.08	-0.39	-0.99	0.13	0.08	$\{a_3, a_4\}$	a_4	50	50	-1
...
99	0.98	-0.39	-0.99	0.00005	0.98	$\{a_4\}$	a_4	-200	50	10

Table 2: Selected points in time of one run, each with the current values

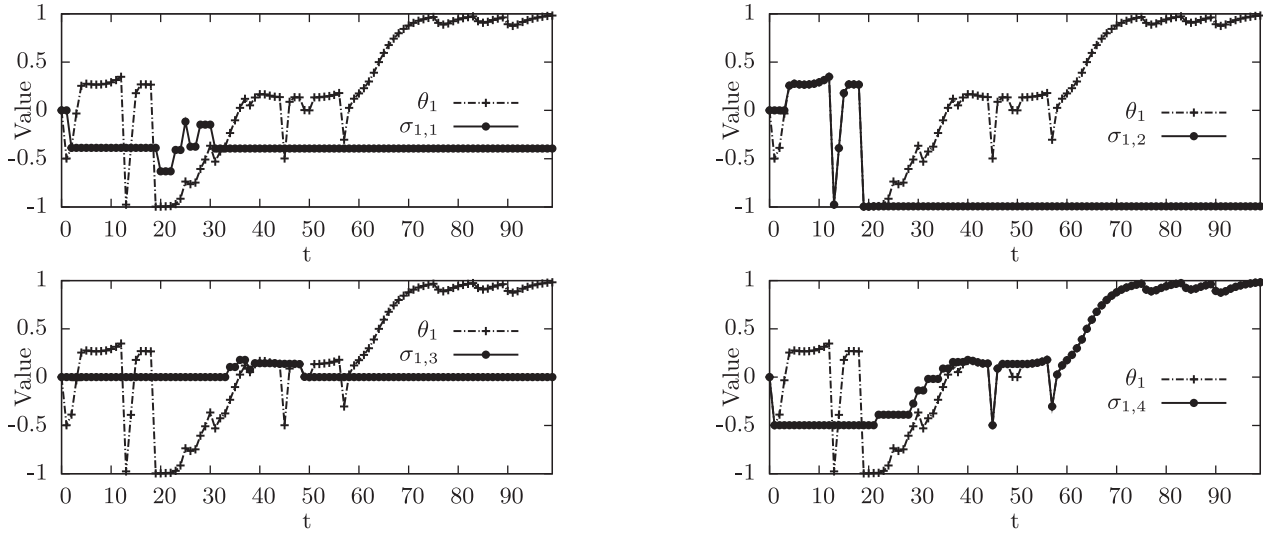


Figure 2: Show the threshold and *Somatic Markers* for the presented example. The threshold is the same for every *Somatic Marker*. When the agent decided to choose only action a_4 the values θ_1 and $\sigma_{1,4}$ are equal.

Example Case

For the presented example table 2 shows values of selected points in time. As described before, every action will be executed once before the algorithm starts at $t = 4$ with the selection based on the equations (14) (16) (18). It could be observed that healthy people show an early preference for *deck A* or *B*, but later change their preferences to the advantageous decks (Damasio 1994). The reason could be that the immediate reward of *deck A, B* is higher than in *deck C* and *D*. Also, the modelled agent shows an early preference for *deck B* until in $t = 18$ the penalty makes all actions available in the next step. Figure 2 shows that this happened before at $t = 13$ but the agent randomly chose *deck B* again. The last time that a disadvantageous deck can be chosen is at $t = 45$ after receiving a penalty at $t = 44$, but the advantageous *deck D* is randomly chosen. From this point only choices between the advantageous *decks C* and *D* are possible. Later on A' only contains a_4 , which leads to the final state shown at $t = 99$. Figure 3 shows all selections in con-

trast to a typical result of the original experiment (Bechara et al. 1994). In both cases preferences for advantageous decks are observable after several choices.

Results

In table 3 the overall results are listed. The data for the described mixed deck configuration show that the sum of chosen disadvantageous decks is only 11.18% and so nearly 90% of all decisions rebound on an advantageous deck. When considering only the first 25 choices of every run it is observable that a learning process has taken place. Here the number of choices for disadvantageous decks is 42.12%, hence nearly 50%. If one compares these results with the results of the original experiment (Bechara et al. 1994; Damasio 1994), the similarities can be found in a high preference for advantageous decks. A difference is observable in the distribution of the choices between the advantageous decks. The presented results show that *deck C* is chosen

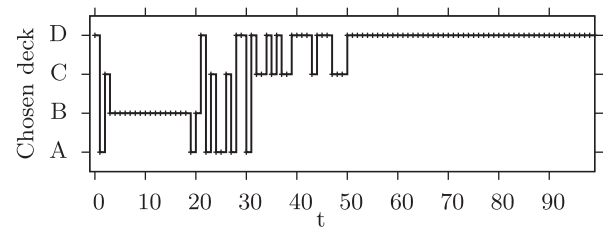
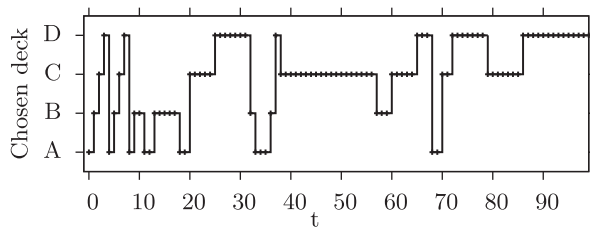


Figure 3: Show the decisions of a typical real subject (Bechara et al. 1994) (left) and the results of the modeled agent (right)

1. Mixed configuration				
	deck A	deck B	deck C	deck D
First 25	438 17.52%	615 24.60%	736 29.44%	711 28.44%
Total	498 4.98%	620 6.20%	6804 68.04%	2078 20.78%
Humans	≈ 14%	≈ 18%	≈ 34%	≈ 34%

2. More frequent penalties with a lower magnitude				
	deck A	deck B	deck C	deck D
First 25	228 9.12%	258 10.32%	974 38.96%	1040 41.60%
Total	228 2.28%	258 2.58%	4404 44.04%	5110 51.10%

3. Less frequent penalties with a higher magnitude				
	deck A	deck B	deck C	deck D
First 25	627 25.08%	689 27.56%	577 23.08%	607 24.28%
Total	689 6.89%	820 8.20%	4171 41.71%	4320 43.20%

Table 3: Results with different configurations of the decks including results for human subjects (Bechara et al. 1994).

nearly 50% more often than *deck D*, although both decks are advantageous decks. However, the original results do not show a significant difference between the numbers of choices of advantageous decks. This effect can be explained by the possible rewards of *deck C*. Either the agent will get a reward of 50 or the reward will be 0. With this configuration the value of the dedicated *Somatic Marker* cannot be negative. If the values of all other *Somatic Markers* are negative, the agent will always choose *deck C*. By changing the configuration of the decks, resulting in equality of possible rewards of the disadvantageous decks and the advantageous decks respectively, it is assured that there is no significant difference between the choices of both advantageous and disadvantageous decks. The configuration with more frequent penalties of a lower magnitude (configuration of *deck A* and *C*) leads to a faster preference of the advantageous decks than the configuration with less frequent penalties of a higher magnitude (configuration of *deck B* and *D*). This is not astonishing as the chance is much higher to receive an early penalty with more frequent penalties. If one compares the two cases shown in figure 3, it is observable that a real subject sometimes chooses from disadvantageous decks even after several decisions while the modelled agent

does not. Of course there are other factors which have an effect on the decision making process like an additional rational analysis of the situation, or personality which can lead to the discussed few choices. Therefore the number of chosen disadvantageous is higher than for the modelled agent. But the preference for advantageous decks can clearly be observed for human subjects as for the modelled agent.

Conclusion

An approach for decision making, consisting of an architecture to model *Somatic Markers* and an algorithm for decision making based on the *Somatic Markers* with no fixed, user given threshold was presented. The results of the modelled agent are comparable to the decision behaviour of human beings. Subsequent work in this field would include concentrating on additional aspects which affect the decision making process, like drives for example. Then applying the approach to a real robot with complex scenarios would be an interesting field of research and an important step towards creating modelled agents capable of making humanlike decisions.

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. 2002. *Socially intelligent agents: creating relationships with computers and robots*. Multiagent systems, artificial societies, and simulated organizations. Kluwer Academic.
- 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.
- 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.
- Winters, P. R. 1960. Forecasting sales by exponentially weighted moving averages. *Management Science* 6(3):324–342.