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Modelling the role of emotion regulation and contagion in socially affected decision making

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Abstract

This paper addresses the role of emotion regulation in a social context by means of a computational social agent model. The model integrates three different phenomena namely emotion regulation, emotion contagion, and emotion-related valuing, in order to analyse the role of emotion regulation in socially affected decision making. The work presented in this paper is illustrated for the interaction between two persons, simulated through agent-based modelling methods. Simulation experiments for different kinds of parameter settings help to understand the underlying mechanism of socially affected decision making and how these decisions can be affected by regulating the emotions involved. Based on the introduced model an ambient intelligent system can be designed to monitor and support a person, for example, to adopt a healthy lifestyle.

Keywords: emotion regulation, decision making, contagion, computational social agent model

1. Introduction

In recent developments on human decision making from a cognitive and neurological perspective the role of emotions has been addressed in more detail. For the case of individual decision making in particular, this concerns the role of emotions in the process of valuing predictions of effects of action options (e.g., [1]). In a social context, often decision making processes of different individuals affect each other, by social contagion processes (e.g., [2]). A specific form of social contagion relevant in such socially affected decision making processes is emotion contagion. By expressing their emotions associated to different decision options, individuals affect other individuals in their emotions for these options. On the one hand this has an instantaneous effect on the choice of an action. On the other hand, through forms of learning, such contagion may also affect decisions made in the future.

The strength of how emotions in an individual develop and are transferred to other individuals (contagion), also depends on the extent to which emotions are regulated. For example, when a person applies a very strong form of emotion regulation so that only a neutral face and body are shown, emotion contagion will not take place, and therefore decision making of others is not affected by such an emotion. Also, for an individual observing the emotion of another individual, if this received emotion is strongly regulated, this may reduce the social effect on the decision making.

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In this paper a social agent model is presented that covers how socially affected decision making relates to emotion contagion in interaction with emotion regulation. First, in Section 2 the model itself is explained in some detail. In Section 3 it is illustrated by means of an example simulation how the model works. Next, in Section 4 more refined explorations are discussed of different scenarios showing the role of emotion regulation in the decision making. Finally, Section 5 is a discussion.

2. Description of the Computational Social Agent Model

As discussed above, not often decisions of an individual are made independent of other individuals, due to the role of social contagion, in particular of emotions related to decision options. Moreover, these emotions usually are also subject to internal regulation processes. To explore the combination of such processes, the social agent model for socially decision making (see Fig. 1 for an overview) presented here is based on the three key principles, namely:

- emotion-related valuing of decision options
- emotion contagion
- emotion regulation

The basic model of decision making based on emotion-related valuing is adopted from the model described in [1]. Also the learning mechanism is adopted from this model. The model for emotion contagion is adopted from [3]. Emotion regulation is based on recent neurological literature which addresses how emotion regulation takes place by an interaction between prefrontal cortex and amygdala [4,5,6,7]. Several findings indicate that less adequate emotion regulation correlates to lower activity in prefrontal cortex areas and less strong connections from amygdala to prefrontal cortex[4]. Moreover, strong indications have been found that REM-sleep strengthens both activation of prefrontal cortex and emotion regulation [8].

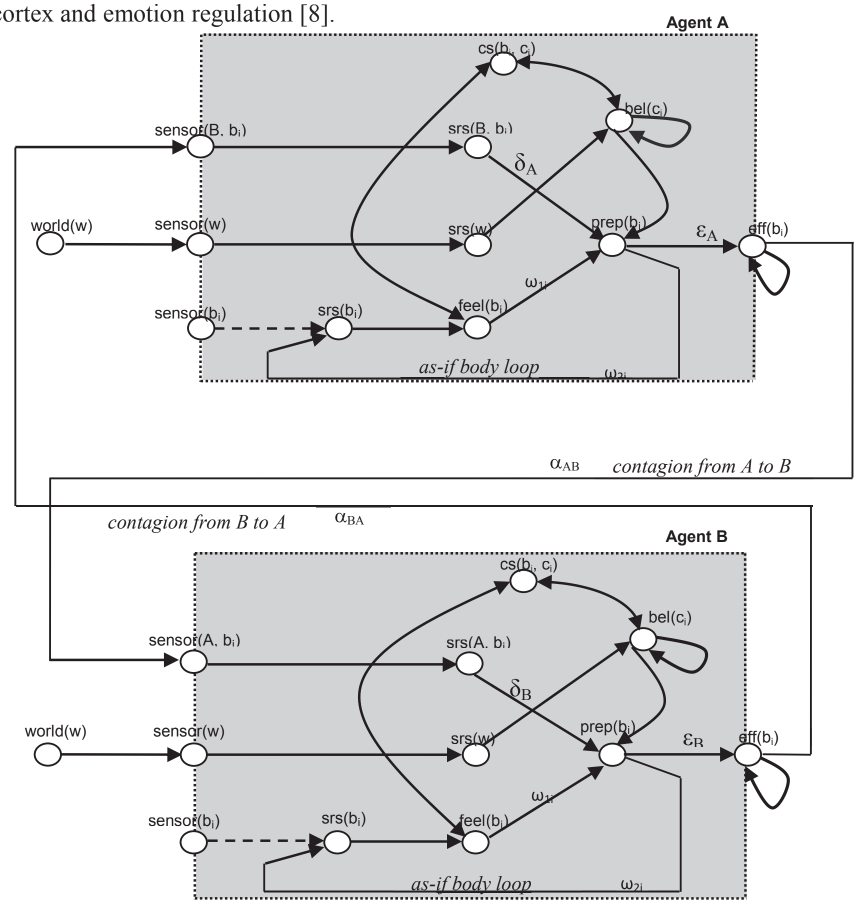

Fig. 1. Overview of the computational model

Although the model is more general, for the sake of simplicity, in this paper only two agents are considered. Agents are described in terms of the dynamics of their internal states, indicated by circles in the dotted boxes, and their interaction states, indicated by circles on the dotted line (see Fig. 1). The sections below elaborate the role of the various internal states of the model.

2.1. World, sensor, and sensory representation states

An agent observes the world state world(w) through the sensor state sensor(w). This world state represents the current situation in which the agent may be facing, for example, boredom, fatigue, or a need to adapt its life style. The very first step in the process is to generate the internal sensory representations of the world state. It depends on the agent that the sensory representation srs(w) is associated to different belief states bel(cj) according to different connection strengths, as some beliefs hold to be true for certain people and for others they might not.

2.2. Beliefs, feelings, preparations, and effector

Belief states bel(c_j) suppress each other through mutual inhibition and influence the decision making process of an agent through different connection strengths to the preparation states prep(b_i) for different options b_i. In order for an agent to internally prepare for a certain action option, it does not only depend on the beliefs but also on the feelings associated with the option. Before performing an action, a feeling state feel(b_i) for the option bi is affected by a predictive as-if body loop[9] via the sensory representation state srs(b_i). This gives a sense of valuing of a prediction about the option before executing an action to perform it. In a scenario where emotion regulation is present, the activation level of the feeling state feel(b_i) also depends on the control state cs(b_i, c_j).

The feeling state feel(b_i) has also an impact on the preparation state prep(b_i), which makes the as-if body loop recursive. The way in which an agent's decision to execute a certain action in the outside world is affected by the (recursive) as-if body loop which portrays the effects of the associated feeling on the preparation of the action option. There may or may not be a one to one correspondence between the beliefs and the feelings. It may be the case that the as-if body loop makes an adjustment of the action option indicated by the beliefs. But in more coherent cases, for example, a strong belief about a decision option b_i may go together with a strong feeling attached to that option and for a weak belief the other way around. It is possible for an agent to have mixed feelings about the different options, but still when it comes to select any one of the two or more mutually exclusive options, by a form of mutual inhibition (by negative mutual connection weights) the effector state eff(b_i) will become significant for only one option. This describes how an agent's feeling and belief play an important role in a decision making process, but if the agent is operating in a social environment then the role of contagion has to be taken into account because it could alter the feelings of an agent.

2.3. Contagion: channel strength, expressiveness, and openness

Within the collective decision making model an additional mechanism for contagion has been incorporated, based on mirroring of the preparation states (adopted from [2]). An important element is the contagion strength γ_{BA} from person *B* to person *A*. This indicates the strength by which a preparation state *S* (for an option b_i) of *A* is affected by the corresponding preparation state *S* of *B*. It depends on characteristics of the two persons: how expressive *B* is, how open *A* is, and how strong the connection from *B* to *A* is. In the model it is defined by

$$\gamma_{BA} = \varepsilon_B \, \alpha_{BA} \, \delta_A \qquad (1)$$

Here, ε_B is the *expressiveness* of *B*, δ_A the *openness* of *A*, and α_{BA} the *channel strength* from *B* to *A*. Note the labels in Fig. 1 for these concepts. The level q_{SA} of preparation state *S* in agent *A* (with values in the interval [*0, 1*]) over time is determined as follows. The overall contagion strength γ_A from the rest of the group towards agent *A* is $\gamma_A = \Sigma_{B \neq A} \gamma_{BA}$. The aggregated impact q_{SA}^* of all these agents upon state *S* of agent *A* is the following weighted average:

$$q_{SA}^*(t) = \Sigma_{B \neq A} \gamma_{BA} \, q_{SB}(t) \; / \; \gamma_A \qquad (2)$$

This is an additional external impact on the preparation state *S* of A, which has to be combined with the impact from the internal emotion-related valuing process. Note that for the case that there is only one other agent, this expression for $q_{SA}*(t)$ can be simplified to $q_{SB}(t)$.

2.4. Emotion Regulation: Control, beliefs, feelings

Over the years several strategies have been proposed in the literature regarding emotion regulation. Broadly speaking, they are categorized into two major types: the ones that can be used before an emotion response has an effect on the behaviour (antecedent focused strategies) and the others in situations where the emotion response already comes into effect after an emotion is generated (response focused strategies) [10]. In the current paper the focus is on antecedent focused strategies. As discussed earlier, a higher activation level of a preparation state $prep(b_i)$ for a certain option b_i depends on the beliefs $bel(c_j)$ and the feeling $feel(b_i)$. Thus, a strong belief supports a choice (b_i) for which a positive feeling exist.

Since in this paper the regulation is based on antecedent focused strategies, the emotion regulation is performed by affecting the following three states of the model: $cs(b_i,c_j)$, $bel(c_j)$, $feel(b_i)$. As discussed earlier, contagion has an important role to play in altering the feelings of a person. The emotion regulation mechanism uses negative weights from the control state $cs(b_i,c_j)$ to the belief state $bel(c_j)$ and the feeling state $feel(b_i)$. Depending on the characteristics of a person the emotion regulation mechanism works strong or less strong (represented by higher or lower values for the negative weights). In simulation scenarios this has been varied for both agents.

2.5. Hebbian Learning

In the model the connection strengths of two types of connections are adapted by Hebbian learning [11]: from preparation state $prep(b_i)$ to sensory representation state $srs(b_i)$, and from feeling state $feel(b_i)$ to preparation state $prep(b_i)$. From a Hebbian perspective, strengthening of a connection over time may take place when both nodes are often active simultaneously ('neurons that fire together wire together'). The principle goes back to Hebb [11], but has recently gained enhanced interest by more extensive empirical support and more advanced mathematical formulations (e.g., [12]). As Hebbian learning depends on the activation levels of the connected states, a positive evaluation of a performed action has a positive effect on the learning, as in this case the sensory representation state $srs(b_i)$ gets a higher activation level. When by the Hebbian learning mechanism the connection strength from $prep(b_i)$ to $srs(b_i)$ has increased, this implies that for a next occasion when the item is encountered the valuing of the option before a decision is made will be higher. Similarly Hebbian learning also enables the feelings for certain option to strengthen with passing time by increasing the connection strength from $feel(b_i)$ to $prep(b_i)$.

For the connections from $prep(b_i)$ to $srs(b_i)$ and from $feel(b_i)$ to $prep(b_i)$ their strengths are adapted using the following *Hebbian learning rule*, taking into account a maximal connection strength 1, a *learning rate* η, and an *extinction rate* ζ (usually taken small):

$$\begin{aligned}\omega\big((prep(b_i), srs(b_i)\big)(t+\Delta t) &= \omega\big((prep(b_i), srs(b_i)\big)(t) \\ &+ \Big[\eta * prep(b_i)(t) * srs(b_i) * \Big(1-\omega\big((prep(b_i), srs(b_i)\big)(t)\Big) - \zeta * \omega\big((prep(b_i), srs(b_i)\big)(t)\Big]\Delta t \qquad (3)\end{aligned}$$

$$\begin{aligned}\omega\big((feel(b_i), prep(b_i)\big)(t+\Delta t) &= \omega\big((feel(b_i), prep(b_i)\big)(t) \\ &+ \Big[\eta * feel(b_i)(t) * prep(b_i) * \Big(1-\omega\big((feel(b_i), prep(b_i)\big)(t)\Big) - \zeta * \omega\big((feel(b_i), prep(b_i)\big)(t)\Big]\Delta t \qquad (4)\end{aligned}$$

A similar Hebbian learning rule can be found in [12, p. 406]. By the factor $1 - \omega(prep(b_i), srs(b_i))(t)$ respectively $1 - \omega(feel(b_i), prep(b_i))(t)$ the learning rule keeps the connection strengths bounded by 1 (which could be replaced by any other positive number); Hebbian learning without such a bound usually provides instability. When the extinction rate is relatively low, the upward changes during learning are proportional to the activation levels of both connected states and maximal learning takes place when both are 1. Whenever one of these activation levels is 0 (or close to 0) extinction takes over, and the connection strength slowly decreases.

2.6. Dynamics of states

The activation level of a state is determined by the impact of all the incoming connections from other states thereby being multiplied by their corresponding connection weights. In particular, for a state causally affected by multiple other states, to obtain their combined impact, first the activation levels V_i for these incoming state are weighted by the respective connection strengths ω_i thus obtaining $X_i = \omega_i V_i$, and then these values X_i are combined, using a combination function $f(X_{1,...,} X_n)$. In the context of current paper the combination function is based on the following logistic threshold function:

$$f(X_1, \dots, X_n) = th(\sigma, \tau, X_1 + \cdots + X_n) \qquad (5)$$

with

$$th(\sigma, \tau, X) = \left(\frac{1}{1+e^{-\sigma(X-\tau)}} - \frac{1}{1+e^{\sigma\tau}}\right)(1 + e^{-\sigma\tau}) \qquad (6)$$

Table. 3 shows which impact contribute to the values of the different states at any time point t as can also be observed from Fig. 1.

Table 1. Overview of the impacts on the states

state	notation	impacts on this state	combined impact values
World state for w	world(w)	-	
Sensor state for w	sensor(w)	world(w)	world(w) · ω(world(w), sensor(w))
Sensory representation for w	srs(w)	sensor(w)	sensor(w) · ω(world(w), sensor(w))
Belief state for c_j	bel(c_j)	srs(w), bel(c_k), cs(b_i, c_j)	srs(w) · ω(sensor(w), bel(c_k)) + bel(c_k) · ω(bel(c_j), bel(c_k)) + cs(b_i, c_j) · ω(cs(b_i, c_j), bel(c_j))
Preparation state for b_i	prep(b_i)	bel(c_j), feel(b_i), srs(B, b_i)	bel(c_j) · ω(bel(c_j), prep(b_i)) + feel(b_i) · ω(feel(c_j), prep(b_i)) + srs(B, b_i) · ω(srs(B, b_i), prep(b_i))
Sensory representation state for b_i	srs(b_i)	prep(b_i)	prep(b_i) · ω(prep(b_i), srs(b_i))
Feeling state for bi	feel(b_i)	srs(b_i), cs(b_i,c_j), cs(b_i, c_k)	srs(b_i) · ω(srs(b_i), feel(b_i)) + cs(b_i, c_j) · ω(cs(b_i, c_j), feel(b_i)) + cs(b_i, c_k) · ω(cs(b_i, c_k), feel(b_i))
Effector state for b_i	eff(b_i)	prep(b_i), eff(b_k)	prep(b_i) · ω(prep(b_i), eff(b_i)) + eff(b_k) · ω(eff(b_k), eff(b_i))
Sensor state for another agent and b_i	sensor(B,b_i)	eff(b_i)	eff(b_i) · ω(eff(b_i), sensor(B, b_i))
Sensory representation state for another agent and b_i	srs(B,b_i)	sensor(B,b_i)	sensor(B, b_i) · ω(sensor(B, b_i), srs(B, b_i))
Control state for b_i and c_j	cs(b_i,c_j)	feel(b_i), bel(c_j)	feel(b_i) · ω(feel(b_i), cs(b_i, c_j)) + bel(c_j) · ω(bel(c_j), cs(b_i, c_j))

3. How does the model work?

This section gives a glimpse of the model by an example scenario. The graphs in Fig. 2 give an idea of how the model behaves when all the elements discussed above are working together to achieve a full process.

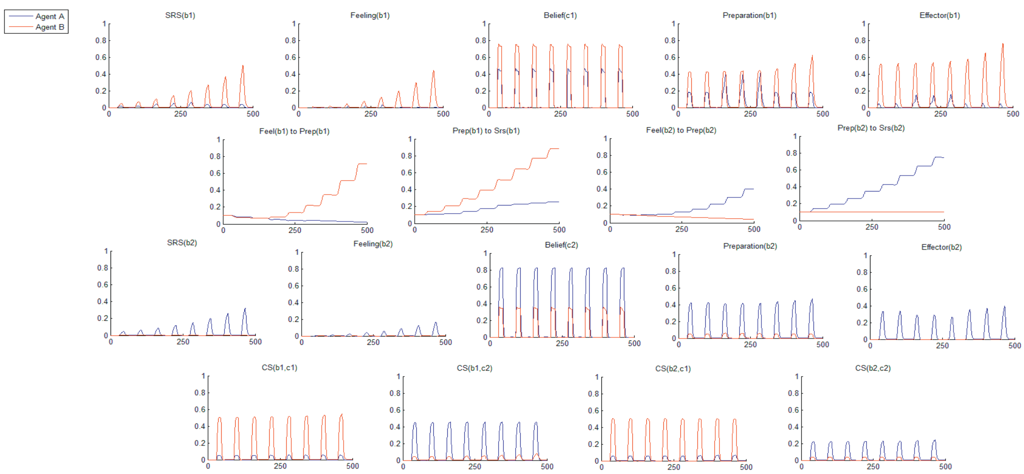

Fig. 2. Emotion Regulation is active in both Agents

In this case b_1 represents a good option. The first row in Fig. 2 represents the activation levels of different states related to option b_1 and the third one to the not so good option b_2. The regulation mechanism in Fig. 2 is active for both agents, and it can be seen that emotion regulation in Agent B (depicted in red colour) suppresses the expressiveness that affects the contagion mechanism which in turn prevents the learning process for the good behaviour (b_1) to take place over a period of time in Agent A (second row in Fig. 2). Emotion regulation works in both agents, which is evident in Fig. 2, showing that Agent A's learning for option b_2 is also affected. The bottom row in Fig. 2 shows the activation levels of control state $cs(b_i, c_j)$; the four graphs represent the control states for the different combinations of feeling (b_i) and belief (c_j).

Furthermore, Fig. 3 shows results without regulation. Here a comparison can be made with Fig. 2 to examine how emotion regulation is able to disrupt the learning process in the context of a social interaction. Fig. 3. shows that the contagion mechanism helps Agent A to gradually adapt to good behaviour (b_1) and even after the contagion is stopped the execution of good behaviour over not so good (b_2) is stronger. Note that the contagion is two way (from B to A and vice versa) as it would be in a real life situation, but it is also assumed in this paper that Agent B has more influence on Agent A than other way around (the channel strength α_{BA} from Agent B to Agent A is assumed higher). The detailed discussion about the simulation results are given in Section 4.

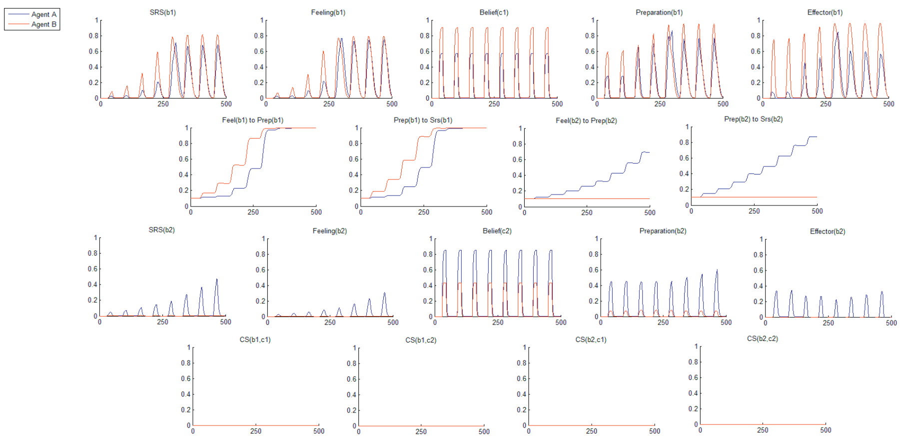

Fig. 3. Effects of contagion without regulation on learning of behaviour

4. Analysis of the Model by Further Simulation Experiments

To analyse the different aspects of the model, a number of more focused experiments have been conducted. As the model combines effects of contagion and regulation, in particular it is of interest to explore in how far the combined effects differ from effects in cases in which only contagion takes place and no regulation. Moreover, relevant effects can be distinguished according to direct effects on behaviour itself and effects on learning of behaviour. Therefore in this section, four simulation experiments are discussed, according to the scheme depicted in Table. 2. Because of the space limitation we can only show the simulation result for the scenario 4.4 (where the regulation works only for agent A).

Table 2. Different types of effects of contagion

	no regulation	regulation
no learning	direct effects of contagion without regulation on behaviour (Section 4.1)	direct effects of contagion combined with regulation on behaviour (Section 4.2)
learning	effects of contagion without regulation on learning of behaviour (Section 4.3)	effects of contagion combined with regulation on learning of behaviour (Section 4.4)

In order to understand the scenario the following real life situation is considered, a situation where the model could be applicable.

> People often feel tired when they return home after work. Different kinds of activities are possible to relax body and mind so that one can prepare for the next day's routine! In the current scenario only two options are considered (to avoid a complex scenario, although more than two options are possible in a real life situation) to be available to the persons. The option are: choice 1, stay at home and watch TV or choice 2, to relax body and mind with some physical activity going for exercise at the nearest sport school. The scenario assumes that two persons interact with each other through some kind of social media. Person 1 is sitting on the couch after a hectic working day; it seems watching TV is a good option for her and initially she decides to stay at home but after being affected by a friend she chooses for the sport school.

4.1. Direct effects of contagion without regulation on behaviour

Two agents play their part in the scenario. In the graphs, states of Agent A are depicted in a blue colour and the other one (Agent B) in a red colour. Settings for the parameter values and for the weights are given in Table 3. Values for threshold and steepness parameters are specified in Table 4. Note that by assigning zero weights from $\mathsf{cs}(b_i, c_j)$ to $\mathsf{bel}(c_j)$ and $\mathsf{feel}(b_i)$ it is realised that no regulation takes place. The initial values of the states are set to 0, learning connections (from $\mathsf{prep}(b_i)$ to $\mathsf{srs}(b_i)$ and from $\mathsf{feel}(b_i)$ to $\mathsf{prep}(b_i)$) usually start at 0.1. As Fig 1. shows, the world state $\mathsf{world}(w)$ triggers some action options in each agent. Initially for Agent A option 2 dominates, and for the second Agent B it is the other way around. These tendencies relate to the specific connection settings between the sensory representation, belief and the preparation states, as can be seen in Table 3. The agents have also feelings associated with both choices, based on similar kinds of weight values given in Table 3. For example, Agent B has a strong emotional association with option 1. Interaction between the agents depends on the channel strength α_{BA}, and also on the degree to which an agent is open for influences of others in general (openness δ_A). Interaction starts during time 150 and 300 Agent B affects Agent A positively for option 1. Agent A indeed takes over the choice for option1. But fully this depends on Agent B's presence. As soon as the interaction between the agents ceases to exist (after time point 300), Agent A swings to option 2 again. 4.2 Direct effects of combined contagion and regulation on behaviour.

In a different scenario with the same settings but this time with regulation realised by settings (refer to Table 3.) The other settings are the same. Identical to the above case in Section 4.1, the contagion starts during the same time period but now in the presence of a regulation mechanism. Note that this mechanism works in both agents. Within both agents it makes the activation levels of feelings lower. In the appendix A[†] also results are presented where it (regulation) works only for one agent. Regulation within both agents takes place based on the control states $\mathsf{cs}(b_i, c_j)$. Appropriate combination of $\mathsf{cs}(b_i, c_j)$ is required to control the feelings for the specific option. For instance if there is contagion for option 1 than control of the feeling for that option is active. The parameter values to control the feelings towards different options are given in Table 3. For this case in the presence of regulation contagion has no decisive effect on behaviour.

4.2. Effects of contagion without regulation on learning of behaviour

In this section we discuss role of contagion on learning of behaviour, as it can be seen from the Fig 1. that we have two learning connections. The first one is between preparation state $\mathsf{prep}(b_i)$ and sensory representation $\mathsf{srs}(b_i)$ and the second one is between feeling state $\mathsf{feel}(b_i)$ and $\mathsf{prep}(b_i)$. The learning process starts from very low values (initially set at 0.1 for both connections) but as the contagion starts to take place, the learning for Agent A gradually increases from lower to higher strengths. It is observed in Agent A that, when the contagion process is stopped after time 300 activation level for $\mathsf{prep}(b_1)$ and $\mathsf{eff}(b_1)$ is higher than before the time point 150. For both connections learning rate η is 0.25, and extinction rate ζ is 0.0001 rest of the other parameter values are same as in the above scenario. In the subsequent section we see how can a regulation mechanism disrupt the learning of a behaviour.

[†] Please refer to following URL for additional simulation results: http://www.few.vu.nl/~amr211/

4.3. Effects of contagion combined with regulation on learning of behaviour

The aim of this experiment is to observe the role of learning in the presence of regulation. As with the previous cases contagion takes place between the time point 150 and 300. All the parameter values are identical to previous scenarios. The model has two learning connections, one is between $\text{feel}(b_i)$ and $\text{prep}(b_i)$ state and the other one is between $\text{prep}(b_i)$ and $\text{srs}(b_i)$. The connections between these pair of nodes are based on the Hebbian leaning principle, therefore when both the nodes are active simultaneously learning is strengthen. The learning rate and the extinction rate for both connections are 0.25 and 0.0001, respectively. The learning connections shape the decision making process. When agent A is influenced by agent B to adapt the good behaviour , and if the regulation mechanism is functioning for agent A then the learning would not have much effect on behavior of the agent and hence the agent is not affected by the influence. Fig. 4. shows a scenario in which regulation is active in Agent A, because of this regulation mechanism the learning of behavior does not take place in its entirety (as can be seen in the second row of the Fig. 4.) besides, it also has a strong effect on option 2 as the Fig.4. illustrates that activation levels of states $\text{prep}(b_2)$ and $\text{eff}(b_2)$ are very low. Note that scenarios in which the regulation takes place for Agent B or both Agents are given in appendix A at URL http://www.few.vu.nl/~amr211/.

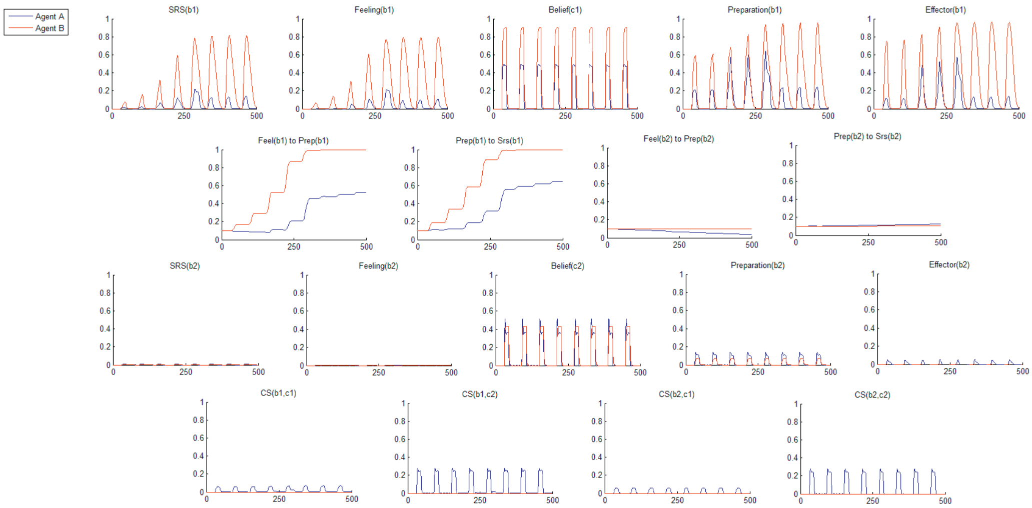

Fig. 4. Effects of contagion and learning in Agent A in the presence of regulation mechanism

Table 3. Connections strengths used in the simulation scenario

From \ To	world(w)	ss (w)	srs(w)	bel(c_j)	prep(b_j)	eff(b_i)	ss(b_i)	srs(b_i)	feel(b_i)	ss(X, b_i)	srs (X,b_i)	cs(b_i, c_j)
world(w)		1										
ss(w)			1, 1 1, 1									
srs(w)				0.5, 0.8 0.9, 0.4								
bel(c_j)				-0.1, -0.1 -0.1, -0.1	0.9, 0.8 0.9, 0.5							0.1, 0.5 0.1, 0.5 0.5, 0.1 0.5, 0.1
prep(b_j)						0.8, 1		0.7, 0.9 0.9, 0.7				
eff(b_i)						-0.4, -0.4 -0.4, -0.4				0.4, 0.9		
ss(b_i)												
srs(b_i)									1, 0.6 0.9, 0.6			
feel(b_i)					0.7, 0.9 0.9, 0.7							0.1, 0.1 0.1, 0.1 0.1, 0.1 0.1, 0.1
ss(X,b_i)											1, 1	
srs(X,b_i)					0.9, 0.5							
cs(b_i, c_j)				-1, -1 -1, -1 -1, -1 -1, -1					-0.1, -0.1 -0.1, -0.1 -0.1, -0.1 -0.1, -0.1			

The first row of each cell represents the values belonging to *agent A* and the second row to *agent B*. If the regulation is on, then values are set appropriately from cs(b_i, c_j) to bel(c_j), feel(b_i) and vice versa, alternatively they are all set to zeros. For the cases in which learning of behaviour is involved, from feel(b_i) to prep(b_i) and from prep(b_i) to srs(b_i) are initially assigned “0.1”. The value for update speed parameter for all states is “0.5”.

Table 4. parameter values used in the simulation scenario

	prep	srs(b)	feel	bel1	cs(b_i, c_j)	effector	ss(X,b_i)	srs(X,b_i)
τ	4	3	4	4	4	6	3	3
σ	0.7	0.3	0.3	0.2	0.2	0.4	0.4	0.4

5. Discussion

In this paper the role of emotion regulation in socially affected decision making processes was addressed. As a point of departure, decision making is assumed to be based on valuing of predictions involving feeling states generated in the amygdala [9]. The presented model is adaptive based on Hebbian Learning [11]. The model can prove to be useful in circumstances where it is important to get rid of bad habits and adapt a healthy lifestyle. Analysis of the model is done using different scenario settings. For instance it is observed in a simulation trace that the emotion regulation mechanism does not only control the feelings and beliefs of agents in a non-learning context, but it is also effective in an environment where learning of behaviour occurs over a certain period of time.

In this paper a generic emotion regulation mechanism is assumed, but in future work perhaps it would be interesting to include the emotion regulation to control specific kinds of feelings, for instance to differentiate negative feelings from positive and making regulation specific to a particular kind of feeling. Another future direction would be to consider a reward mechanism after an action has been performed, as decisions related to a particular choice are often based on a prediction of a rewarding or aversive consequence experienced in the past. This addition to the model could prove to be useful because in decisions such an emotional valuing often plays an important role. It would also be interesting to study the role of emotion regulation within such a reward mechanism. The current model may be used as a point of departure for this.

Ambient intelligence and affective computing paradigms provide the perfect settings for the scenario and model presented in this paper to materialize it in terms of an application that can provide personalized support on the basis of an individual's affective state. In addition, it can also suggest appropriate interventions required to help people in a social network to improve their physical activity level. For example, identification of individuals in a social network that could motivate and support a person (who is not so motivated) to join a sport school or exercise regularly in order to improve physical health.

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