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Dynamics of a computational affective model inspired by Dörner's PSI theory

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Abstract

The PSI theory of Dietrich Dörner touches a number of questions, especially about knowledge representation, perception and bounded rationality. However, since it is formulated within psychology, it has relatively little impact on the discussion of emotion modeling within computer science. This paper introduces a computational model for emotion generation and function by formalizing part of Döner's PSI theory. We also borrowed some technical ideas from MicroPSI, one of the concrete implementations of PSI theory by Joscha Bach. Based on this computational model, a number of simulation experiments have been performed and evaluated. The experimental results show that the emotions of agents controlled by our proposed model can emerge from the interaction between the agents and the environment. Then the dynamics of this computational model are studied using Lewis's dynamic theory of emotions. We successfully found hints of phase transitions in the emotional changes, including trigger, self-amplification and self-stabilization phases, as suggested by Lewis. Based on these simulation results, we argue that this computational model is a quite promising approach of modeling both emotion emergence and dynamics.

Keywords: Emotion modeling; PSI theory; Dynamic systems

1. Introduction

In the last decade, affective computing has proven to be a viable field of research comprised of a large number of multidisciplinary researchers resulting in work that is widely published and used (Broekens, 2010). A large body of researchers have studied automatic emotion recognition (Fasel & Luettin, 2003; Fragopanagos & Taylor, 2005; Hanjalic & Xu, 2005; Picard, 2003) and computational modeling of casual factors of emotion for human–computer (Bickmore & Picard, 2005; Hudlicka, 2003; Paiva, 2000) and human–robot interaction (Breazeal, 2003; Fong, Nourbakhsh, & Dautenhahn, 2003). However, only a small part of affective computing community is explicitly concerned with modeling the effects of emotion, such as affective influences on cognition (Canamero, 2002; Gadanho, 2003; Hudlicka, 2005; Marsella & Gratch, 2009; Velsquez, 1998), formal modeling of cognitive appraisal theory (Broekens, DeGroot, & Kosters, 2008; Marsella & Gratch, 2009; Meyer, 2006), interacting emotional states in agent

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reasoning (Coddington & Luck, 2003; Meyer, 2006; Steunebrink, Dastani, & Meyer, 2008) and models of emergent emotions, such as emerging from the interaction between a simple adaptive agent and its environment (Canamero, 2002; Lahnstein, 2005; Velsquez, 1998).

This article introduces a computational model inspired by PSI theory, proposed and described informally by German psychologist Dietrich Dörner (Dörner, 2003; Dörner & Hille, 1995; Dörner & Starker, 2004; Dörner, Gerdes, Mayer, & Misra, 2006). The PSI theory adopts many ideas from different disciplines, such as dynamical system theory, neural networks, semantic nets, functionalist and structuralist foundations, contemporary theory of perception, emotion and action control that developed by Dörner himself. It covers a wide range fields of intelligence, including knowledge representation, perception and bounded rationality. However, we mainly focus on its emotional model, which is quite different from other affective models like OCC (Ortony, Clore, & Collins, 1990). Emotion in PSI theory, is not considered as an isolated component, instead, it emerges from the interaction between the agent and the environment where the agent lives. The agent controlled by the PSI model is considered as an autonomous machine driven by internal motives that are connected to urges, which stand for physiological, cognitive or social demands. Then emotions, in PSI model, are derived from the dynamics of the whole system, where the processes of perception, cognition and action selection interact with each other.

The work described in this paper is not the first attempt to formulate the original PSI theory, which is formulated within psychology and has relatively little impact on the subject of emotion modeling within computer science. Joscha Bach, for instance, has extended the original PSI theory and implemented a concrete model named MicroPSI (Bach, 2003, 2008; Bach, Dörner, & Vuine, 2006). Many of his work has been described in his book (Bach, 2008) in detail. However, the dynamics of the PSI theory has not been thoroughly discussed yet. So the main purpose of this article is to study the aspects of dynamics and emergence of the PSI model. Firstly a computational model based on PSI theory is implemented and then a bunch of experiments are performed on our computational model, and finally the experimental results are carefully analyzed by one of the contemporary dynamic theories of emotions proposed by Lewis.

Lewis, like Dörner, holds a non-linear, dynamic view of emotional activations (Lewis, 2000, 2005). He argues that emotions should be considered as phenomenon, which emerges from the dynamics of the whole system. He suggested that emotion-appraisals may be conceived as phase transitions including trigger phase, self-amplification phase and self-stabilization phase. Once triggered, recurrent interactions between microscopic processes of emotion appraisal induce a rapid self-amplification effect on the activity of the interaction of the appraisal-emotion constituents of the system. Positive feedback loop between perceptual, emotional and attentional processes are firstly lured by the self-amplifying phase but then inhibited or constrained by negative feedback effects as the amplification grows. When negative feedback overtakes the system dynamics, the appraisal process enters self-stabilization phase, where change decreases and continuity increases.

Our simulation results show that the computational model proposed in this paper is a quite promising approach of emotions modeling, since phase transitions suggested by Lewis could be observed in our experimental results. Two reasonable relations between emotional levels and resource allocations in the environment are also found, which comply with our common sense quite well but are not predefined in the affective model.

In Section 2, the PSI theory, especially the emotion model of it, is explained in detail. In Section 3, dynamic theories of affective models are discussed. In Section 4, the computational model based on PSI theory is described in detail. Section 5illustrates the model by a number of simulation experiments with different environmental settings. Section 6 concludes the paper with a discussion, comparison with other cognitive models, and future work. The emotion model is currently applied in a very simple scenario, latter on, it should be verified by applying to NPCs (non-player characters) in a more complex game world or even social robot in the real world.

2. PSI theory

2.1. Global overview of PSI theory

The most distinctive feature of PSI theory is its perspective on the autonomous choice and regulation of behaviors. It suggests that each goal-directed action has its source in a motive that is connected to an urge, which stands for a physiological, cognitive or social demand (Bach, 2009). When a positive goal is reached, a demand may be partially or completely fulfilled, which creates a pleasure signal that is used for learning, by strengthening the associations of the goal with the actions carried out and situations that have led to the fulfillment.

In order to verify the ability of the PSI model, Dörner also implemented virtual agents controlled by PSI living within a complex simulated game world (Fig. 1). These PSI agents are little virtual steam vehicles, which depend on fuel and water for their survival.

A PSI agent does not need any executive structure that controls its behavior, instead it is driven by demands. A limited number of basic needs are modeled through homeostatic variables. Some of the demands related to external resources, such as energy and water, or its integrity. However, there are also abstract cognitive demands, like certainty and competence, while the affiliation demand is an example of social urge, which can only be fulfilled by other agents. In addition there is a threshold for each demand. A deviation from the threshold set for a need will signal as an urge, which then give rise to an intention or a motive. There may be multiple motives at any given time but only

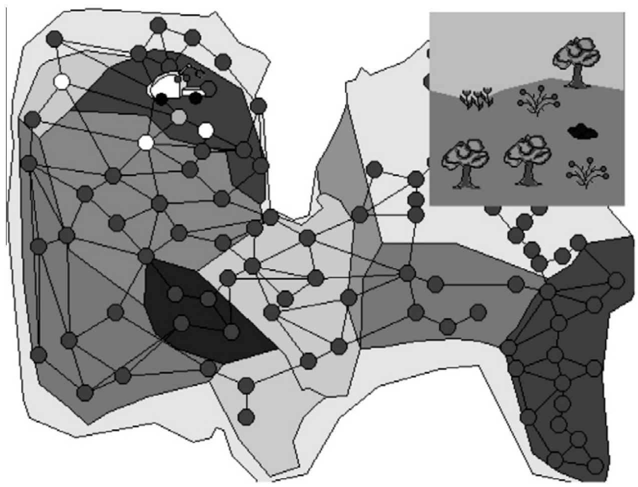

Fig. 1. The PSI agent and the island, adopted from Dörner (2003).

one "ruling motive" dominates the system. The active motive is selected based on the strength of the urge and the estimated chance of realization.

After selecting a motive intention, actions of the agent are produced according to the active motive. A PSI agent has three stages for handling the selected intention.

- Firstly, the agent tries to recall an automatic, highly ritualized reactions base on the intention from its memory.
- If no such reaction exists, it attempts to construct a plan, utilizing existing knowledge in its memory.
- Once both automatic and planning fail, the agent resorts to exploration by applying trial and error.

Perception, which is derived from the environment and the actions being executed on it, forms the agent's situation image, a description of the present situation. There are links connecting these situation images. The strength of the links depend on the motivational relevance of the event in the current situation (Fig. 2). Whenever a demand is satisfied the links of the current situation to its immediate past are strengthened, so that relevant situations become associated both to the demand and the sequence of events that lead to the satisfaction of the demand. As a result, "islands" of related events appear in the agent's long term memory, which can be used for planing later.

PSI agents are based on something like a "sense-think-act" cycle, but perception, planning and action do not occur in strict succession. Instead they are working as parallel processes and are strongly interrelated. All actions of agents happen due to motivational impulses, which are derived from a set of predefined dynamic demands. Perception, memory retrieval and action control strategies are influenced by modulator parameters, which make up a setting that can be interpreted as an emotional configuration (Fig. 3).

Dörner has suggested four modulators:

- *Activation* is the preparedness of perception and reaction. It makes the agent balance between rapid, intensive activity and reflective, cognitive activity. Fast behavior comes along with high level activation and becomes slower with decreasing level of activation.
- *Resolution level* determines the accuracy of cognitive processes including perception, planning, action regulation etc. It decrease with increasing activation. For instance, when an agent gets angry (with high activation), it would probably not give careful consideration to the consequence of its action (with low resolution level).
- *Securing threshold* controls the frequency of securing behavior, which is implemented as a series of behavior programs that check unexpected changes in a dynamic environment. The securing threshold is proportional to the strength of the current motive, that is there will be less securing behavior (with high securing threshold) in

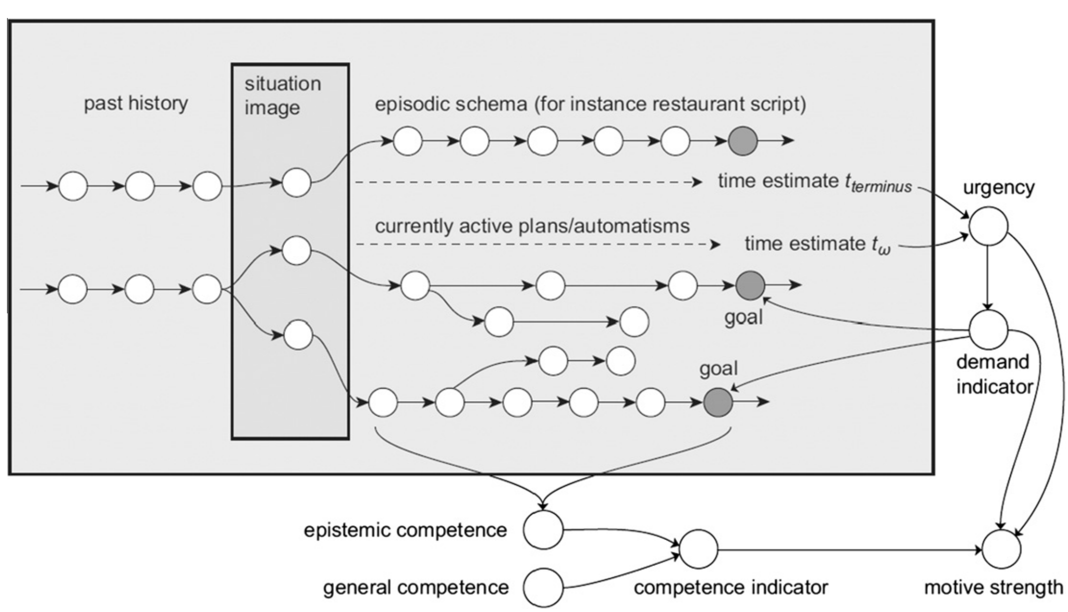

Fig. 2. Perception and motives, adopted from Bach (2009).

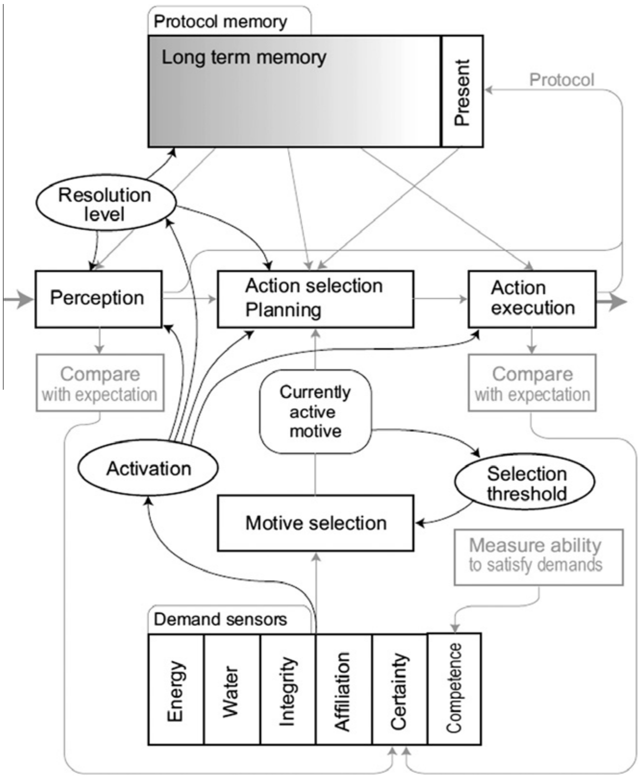

Fig. 3. PSI architecture, adopted from Bach et al. (2006).

the face of urgency. It also depends on agent's certainty of current situation. An undetermined environment requires more securing behavior (with low securing threshold).

- *Selection threshold* indicates how easily the agent switches between conflicting intentions. It prevents oscillation of behavior by giving the current leading motive priority. It increases with heightening activation. For example, when escaping threats (with high activation), the agent is highly concentrated on current integrity demand (with high selection threshold).

2.2. The emergence of emotions in PSI model

As we know, the OCC (Ortony et al., 1990) model has established itself as the standard model for emotion synthesis. Since the OCC model describes a concise hierarchy of 22 emotions and specifies the conditions of each emotions in terms of objects, actions and emotions, it could be easily described in formal language. A number of computational models have been proposed by formalizing the OCC model, such as Kshirsagar (2002), Egges, Kshirsagar, and Magnenat-Thalmann (2003), Liu and Pan (2005), Gebhard (2005), Katsionis and Virvou (2005).

However, unlike these affective models, emotion in PSI model is not considered as isolated component. Instead it emerges from the dynamics of the whole system, where the processes of perception, cognition and action selection controlled by modulators interact together. The very basic idea of emotion in PSI is to define a small set of proto-emotional dimensions in terms of basic demands and modulators. Then all sorts of emotions are recognized as regions in the space spanned by these dimensions.

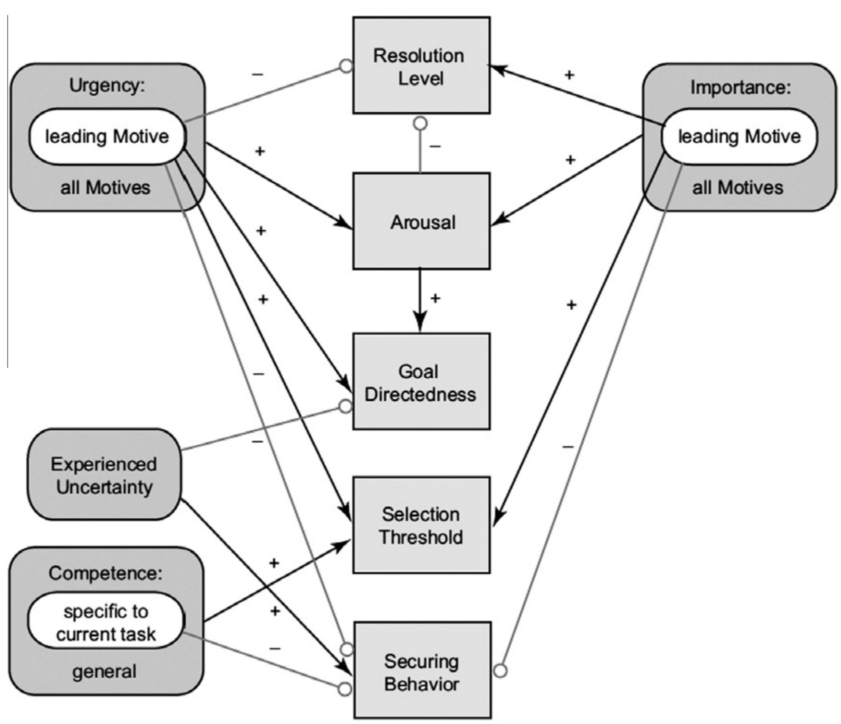

Fig. 4. Dimensions of emotion, adopted from Bach (2009).

For example we can use a six-dimensional continuous space in the simplest approach:

- Pleasure
- Activation
- Resolution level
- Securing threshold
- Selection threshold
- Level of goal-directed behavior

It worth noting that these dimensions are not orthogonal. Fig. 4 shows how they are derived from underlying urges and modulators. For instance, resolution is mainly inversely related to activation.

Then emotions in PSI theory are understood as areas in the multidimensional space. Anger, for example, is characterized by high activation, low resolution, strong motive dominance, few background checks and strong goal-orientedness; sadness by low activation, high resolution, strong dominance, few background checks and low goal-orentedness (Bach, 2009).

However, the six-dimensional model is not exhaustive. When dealing with social emotions, one may wish to introduce demands for affiliation (external obedience to social norms) and honor (internal obedience to social norms), then additional dimensions may be needed.

3. Dynamics of an affective model

Affective computing has been studied for decades. However, many researchers mainly focus on automatic emotion recognition and computational modeling of casual factors of emotions; and only a few of them pay special attention to the dynamics of the cognitive appraisal processes. Scherer and Lewis are two of those researchers interested in the dynamics of emotional models.

Scherer has proposed a "component process model of emotion" (Scherer, 2000) emphasizing continuous evaluative monitoring of the organism's environment. He claims that emotional reactions are "incredibly complex, multi-componential processes that can not be captured and described by verbal labels".

Lewis (2005) like Scherer also holds a non-linear, dynamic view of emotional activations, but criticizes Scherer's process model of emotions on the grounds that it, like many other classical appraisal theories, views appraisal as antecedent to emotion. Lewis espouses the view that emotions are actually both cause and effect of appraisals. Lewis provides a model of "appraisal-emotion amalgams", which places emphasis on the emergence of stable states induced by the effects of negative feedback on the amplifying effect on states receiving positive feedback. This increasingly popular position as to a possible mechanism for the engendering of emotions is similarly described by the neuroscientist:"The basic emotional systems may act as 'strange attractors' within widespread neural networks that exert a certain type of 'neurogravitational' force on many ongoing activities of the brain, from physiological to cognitive." Lowe, Herrera, Morse, and Ziemke (2007).

According to Lewis, "appraisal-emotional amalgams are construed as globally coherent states arising and stabilizing through non-linear casual transactions among appraisal and emotion constituents." Once triggered, recurrent interactions between the microscopic process constituents of the emotion-appraisal amalgams induce a rapid self-amplifying effect on the activity of the interaction of the appraisal-emotion constituents of the system. The self-amplifying effect thus results in positive feedback loop between perceptual, emotional and attentional processes that initially perpetuate the positive feedback effect but are then inhibited or constrained by negative feedback effects as the amplification grows. This chain of events, culminating in a stabilization phase, i.e. phase transition, is referred to by Lewis as Emotion Interpretation or EIs.

We, like Lewis, also argue that emotions should be considered as phenomenon that emerges from the dynamic of the whole system. According to (Smith & Thelen, 2003), for a dynamic system, there are two basic assumptions of its development:

- *Multicausality.* Dynamic systems are complex systems composed of many individual elements, none of which has causal priority. Such systems can exhibit coherent behavior: the parts are coordinated without an executive agent or a programme that produces the organized pattern. Rather, the coherent is generated in the relationship between the organic components and the constraints, and opportunities of the environment. Such self-organized systems are characterized by the relative stability or instability of their states.
- *Nested timescales.* Behavioural change occurs over different timescales. As Table 1 illustrates, emotional episode happens in seconds or minutes, while mood can last for hours or days, and the personality may take years to develop. For the organism, time is unified and coherent, as are the collaborating elements of the system, that is, the dynamics of one time-scale (e.g. emotional episode) must be continuous with and nested within the dynamics of all other time scales (e.g. the changes of mood or the development of personality).

Lewis's dynamical systems approach to emotion-appraisals was conceived as a means of providing a bridge between psychological and neurobiological mechanisms for emotion-appraisal processing. The key ideas of his model are as follows:

- *Trigger phase* is usually the beginning of an appraisal-emotion episode, when the orderly behavior of the system is interrupted by a perturbation, resulting in rapid loss of orderliness and an increase in sensitivity to the environment. Thus a trigger indicates a phase transition, characterized by sudden change and temporary disorder as the system switches to a new organization.

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Table 1
Scales of emotional development (Lewis, 2000).

	Emotional episode	Mood	Personality
Timescale	Seconds, minutes	Hours, days	Years
Description	Rapid convergence of a cognitive interpretation with an emotional state	Lasting entrainment of interpretative bias with a narrow emotional range	Lasting interpretive-emotional habits specific to classes of situations
Dynamic system formalism	Attractor	Temporary modification of state space	Permanent structure of state space
Possible neurobiological mechanism	Cortical coherence mediated by orbito-frontal organization entrained with limbic circuits	Orbitofrontal-corticolimbic entrainment, motor rehearsal, and preafference, sustainded neurohormone release	Selection and strengthening of some corticocortical and corticolimbic connections, pruning of others, loss of plasticity
Higher-order form	Intention, goal	Intentional orientation	Sense of self

- *Self-amplification phase* follows perturbation and nucleation. Then the system enters positive feedback loops. When positive feedback predominates, systems are highly sensitive, that is small deviations may be rapidly amplified.
- *Self-stabilization phase* happens when negative feedback overtakes the system dynamics, change decreases and continuity increases. Dynamics systems principles suggest that the consolidation of coherent emotion-cognitive appraisal states is necessary for complexification, allowing appraisals to become more elaborate and articulated.
- *Learning* cognition-emotion associations that tend to recur in future is the connection between biases, believes, traits, emotional habits and real-time appraisal processes. The self-stabilization phase is the necessary precondition for this learning. When appraisals have stabilized, interpretations, action plans and expectancies endure for some period of time. Then the connectivity among these elements that are reciprocally activated in real time are strengthened, which is responsible for learning.

From Lewis's perspective, emotions can be understood based on the instability of appraisal and emotion response. We argue that different phase transitions among trigger, self-amplification and self-stabilization are the results of multicausality of processes in dynamic systems, and the coherence of emotional process in nested timescales can be achieved by learning.

4. Our computational model in detail

4.1. General architecture

Our proposed model adopts multi-agent architecture, which contains a server called "mind server" and a bunch of "mind agents" running in the server (Fig. 5). For each loop of the "mind server" i.e. "mind cycle", it would check if it is time to execute a specific "mind agent". A "mind agent" is a software object that is intended to act during "mind cycle".

"World Interface", similar to "world adapter" in MicroPSI (Bach, 2003; Bach et al., 2006), provides a generic interface between mind server and outside world, which can be a game world or even the real world. It converts data coming from the world into the format desired by Perception Updater Mind Agent, and encapsulates actions generated by Action Selection Mind Agent into requests sent back to the outside world.

Though the world can be a virtual world or the real world, as an initial step in this paper, we choose a simple game world to verify our computational model. All the avatars controlled by the affective model are living within a simulated game world, depending on food and water for their survival (Fig. 6). There are two tribes in the virtual world. Avatars from different tribes are enemies and may fight for food or water; while avatars within the same tribe are friends and they tend to live together with members in the same tribe, that results in the satisfaction of affiliation demand. When the avatar firstly enters the game world, it has no knowledge of the environment. Then its certainty increases, when exploring the world. Its competence also varies during the interaction with the environment and other avatars. Our proposed model is then applied to model the behaviors and emotional changes of these avatars living in this virtual world.

Regarding to "Knowledge Base", it consists of short term and long term memories, which can be converted to each other to some extend. Short term memory holds the information, such as perception, in an active, readily available state for a short period of time; long term memory contains knowledge, such as rules used for action planning, which may be reusable in future.

We argue that multiple knowledge representations are almost inevitable in practical modeling due to restricted computing resource and time pressure, especially when dealing with the real world. However, it would be convenient to apply data mining or machine learning algorithms to the knowledge base if unified knowledge representation is adopted. So we use hypergraph (Gunopulos, Mannila, Khardon, & Toivonen, 1997; Karypis, Kumar, & Mobasher, 1998; Zass & Shashua, 2008) as unified knowledge representation for long term memory, where data mining and machine learning algorithms mainly apply to, and are open to all sorts of knowledge representations for short term memory, which focus more on efficiency.

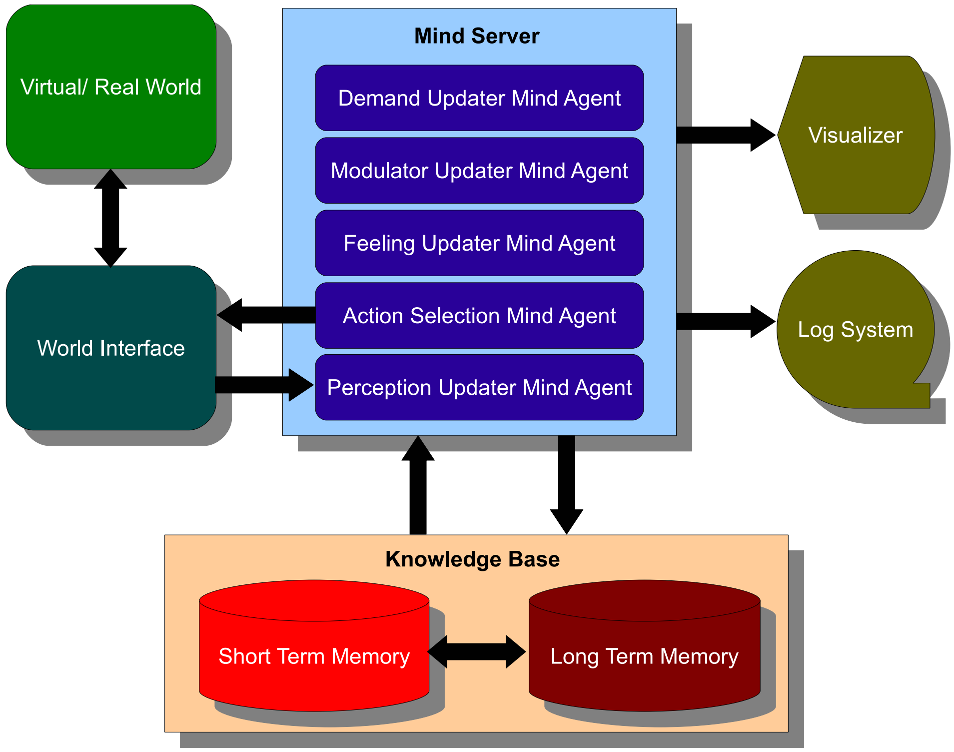

Fig. 5. Framework overview.

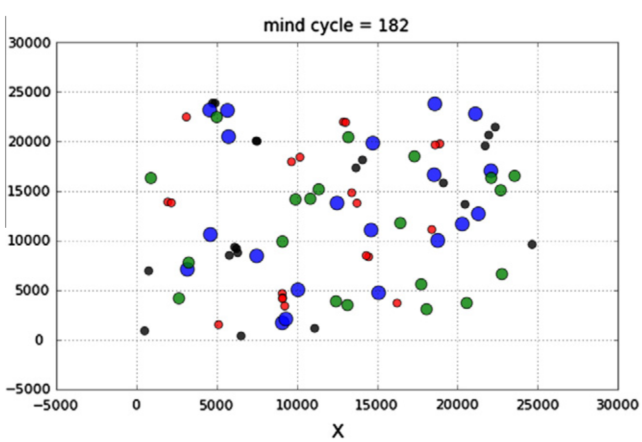

Fig. 6. Snapshot of the virtual world. Blue points stand for water; green ones are for food; red and black dots represent avatars from two tribes respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Technically we tend to use NoSQL database (Leavitt, 2010; Vicknair et al., 2010; Xiang, Hou, & Zhou, 2010) as our concrete knowledge base, which is a broad class of database management systems that differ from currently dominant relational database management systems (RDBSes). Compared with RDBSes, NoSQL database provides flexible data models, and is good at elastic scaling and dealing with dig data. Moreover, many open source NoSQL database management systems, written in popular programming languages, are already available and ready to use (see also http://nosql-database.org/).

Finally, there are two optional subsystems "visualizer" and "log system", which can easily track the changes of internal states within "mind server" and "mind agents". For example, Fig. 7 shows the changes of modulators, demands and feelings in real time from the visualizer. It is quite useful for observing the internal dynamics of the model as the system evolves and also helpful when tuning parameters of the system. In addition, the log system can record even more details in log files, which can be analyzed later. Our experiments in Section 5 take advantages of both.

4.2. Mind agents related to PSI theory

Our proposed model is implemented as five "mind agents" in the architecture described above. Each of them has a specific task, which can hardly produce complex behavior alone. However, as illustrated in Fig. 8, they closely interact with each other, which would result in much more complicated and interesting behavior. Then the emotions emerge from the dynamics of both internal changes, and the interaction between the system and the environment. Remaining part of this section will describe all these "mind agents" in detail.

DemandUpdaterMindAgent is in charge of updating a fixed set of demands of the avatar living in the virtual world, and the primary goal of the avatar is to maintain these demands within certain ranges.

For each demand (d), it comes along with a minimum and maximum level (min_l and max_l), then the

Fig. 7. Visualizer of internal states, including levels of demands, modulators and feelings.

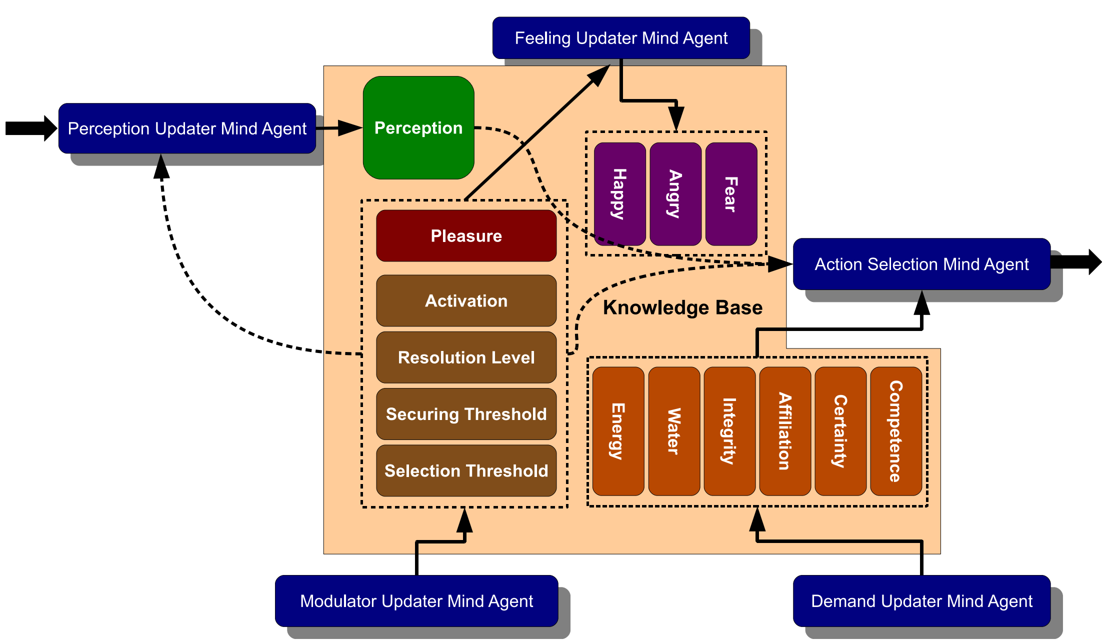

Fig. 8. PSI related mind agents.

satisfaction (S) of the demand can be derived from current level (L) using simple fuzzy formulas,

$$S_d(L, min\_l, max\_l, \alpha) = \begin{cases} fuzzy\_equal(L, min\_l, \alpha), & L < min\_l, \\ 0.9 + 0.1 * random(0,1), & L > max\_l, \\ 0.8 + 0.2 * random(0,1), & otherwise. \end{cases} \quad (1)$$

Where *fuzzy_equal* is defined as

$$fuzzy\_equal(x, t, \alpha) = 1/(1 + \alpha * (x - t)^2) \quad (2)$$

$random(0,1)$ generates random numbers in [0,1]. When $L > max\_l$, $0.9 \leqslant S\_d \leqslant 1.0$; when $min\_l \leqslant L \leqslant max\_l$, $0.8 \leqslant S\_d \leqslant 1.0$.

α is a parameter, which controls how fast the *fuzzy_equal* output decreases when x deviates from t. Larger α results faster decrease. In our experiment we choose $\alpha = 150$.

It should be noted that, unlike PSI or MicroPSI, in our model, the target ranges of demands are not fixed, instead, they hold initial values and then can be updated based on the interaction between avatar and the environment (formula (3) and (4)). The very basic assumptions is that the avatar would expect even more if a specific demand is satisfied and may tend to restrain themselves when the related resource of the demand is not easily reachable. As the system evolves, the personality of an avatar could be leaned from appraisal processes.

$$min\_l(t+1) = \begin{cases} \beta \cdot min\_l(t) + \delta, & demand\ is\ satisfied, \\ \beta \cdot min\_l(t), & otherwise. \end{cases} \quad (3)$$

$$max\_l(t+1) = \begin{cases} \beta \cdot max\_l(t) + \delta, & demand\ is\ satisfied, \\ \beta \cdot max\_l(t), & otherwise. \end{cases} \quad (4)$$

Regarding to the demand levels, many physiological demand levels can be retrieved directly from the world interface, while levels of more abstract demands, such as affiliation, certainty and competence, are calculated based on the environment or avatar's experience.

Formula (5), (7) and (9) are tentative equations of updating affiliation, certainty and competence demands, which are currently adopted in our model. In formula (5), d_i is the distance between friend i and the avatar itself, d_{max} is a distance threshold to decrease influence of friends far away. For formula (7), t_i is the latest time stamp of observing object i and t_s is the current time stamp of the virtual world.

$$L\_affiliation = \frac{\sum_{i=1}^{friend\_num} fuzzy\_near(d_i, d_{max}) + random(0,1)}{(1 + exp(-0.1 * friend\_num)) * (friend\_num + 1)} \quad (5)$$

$$fuzzy\_near(d_i, d_{max}) = 1/(1 + 0.00015 * (d_i - d_{max})) \quad (6)$$

$$L\_certainty = \frac{\sum_{i=1}^{object\_num} fuzzy\_new(t_i, t_s) + random(0,1)}{(1 + exp(-0.05 * object\_num)) * (object\_num + 1)} \quad (7)$$

$$fuzzy\_new(t_i, t_s) = 2/(1 + exp(0.002 * (t_s - t_i))) \quad (8)$$

$$L\_competence(t+1) = \begin{cases} L\_competence(t) * 0.95 + 0.05, & action\ at\ time\ t\ succeeds, \\ L\_competence(t) * 0.95, & action\ at\ time\ t\ fails. \end{cases} \quad (9)$$

ModulatorUpdaterMindAgent would update modulators during "mind cycle". Modulators are considered as parameters that control both cognitive and emotional processes. Moreover, they are closely related, thus result in the inherent dynamics of the system.

We suggest using a group of formulas below to update the modulators.

$$activation = S_{certainty} * (1 - \sqrt{S_{competence}}) \quad (10)$$

$$resolution\_level = 1 - \sqrt{activation} \quad (11)$$

$$securing\_threshold = normalize\left(\frac{1 + S_{certainty}}{1 + S_{current\_demand}}, 0.5, 2\right) \quad (12)$$

$$selection\_threshold = clip\_within((selection\_threshold + 0.5) * (activation + 0.5), 0.001, 1) \quad (13)$$

Where *normalize* and *clip_within* are defined as,

$$normalize(x, min, max) = (x - min)/(max - min) \quad (14)$$

$$clip\_within(x, min, max) = \begin{cases} min, & x < min, \\ max, & x > max, \\ x, & otherwise. \end{cases} \quad (15)$$

Activation is related to certainty and competence demands (formula (10)), that is, the avatar will be more ready to react (higher activation), when it is more familiar with the environment (higher $S_{certainty}$) and feels more confidence of its ability (higher $S_{competence}$).

Resolution level is mainly reverse to activation (formula (11)), which means if the avatar is more ready to execute an action (higher activation), it will spend less energy in cognitive processes (lower resolution level), such as perception, action planning etc.

Securing threshold is influenced by satisfactions of certainty demand and currently selected demand (formula (12)). When the avatar knows more about the environment (higher $S_{certainty}$) or is not satisfied with the current demand (lower $S_{current\_demand}$), it would tend to more securing behavior (lower securing threshold).

Selection threshold is proportional to activation and its previous value (formula (13)). When the avatar focuses more on executing current action (higher activation), the probability to discard the current action (or plan) should be low (higher selection threshold).

ActionSelectionMindAgent starts from a demand and tries to figure out a chain of actions that would probably lead to the satisfaction of the demand. Selection threshold has impact on choosing active intention. The pseudo code below presents a simple mechanism currently used.

```
IF random (0,1) < selection_threshold
   Select the demand with lowest
 satisfaction
ELSE
   Randomly pick up a demand
```

PerceptionUpdaterMindAgent renews the perception of the environment. The perception process is modulated by resolution level. Since this mind agent closely related to the environment, the concrete implementation depends on the outside world. For instance, in our simple virtual world, the resolution level has impact on the range of virtual field. Higher resolution level comes along with a larger visual field, which would make the avatar take more effort to explore the environment.

FeelingUpdaterMindAgent updates the emotional states of the avatar based on modulators and pleasure. Since these modulators control the dynamics of the whole system, emotional changes derived from modulators naturally embody system dynamics.

For each kind of emotion (E), its intensity (I) can be calculated from modulator (m) levels

$$I(E) = \sum_{m,i_m \neq U} W_m * P(m, i_m)$$
$$(i_m = H, L, M, EL, EH, U) \tag{16}$$

W_m is the weight of modulator m. P is a simple fuzzy logic function that outputs a number within [0,1] according to the modulator level m and its corresponding indicator i_m. The indicator that controls the calculation of P can be H (high), L (low), M (medium), EL (extremely low), EH (extremely high), and U (undefined).

More specifically, we suggest P as

$$P(m, i_m) = \begin{cases} fuzzy\_low(m, 0.15, 150), & i_m = EL, \\ fuzzy\_low(m, 0.30, 150), & i_m = L, \\ fuzzy\_equal(m, 0.50, 150), & i_m = M, \\ fuzzy\_high(m, 0.70, 150), & i_m = H, \\ fuzzy\_high(m, 0.85, 150), & i_m = EH, \\ 0, & i_m = U. \end{cases} \tag{17}$$

$$fuzzy\_low(x, t, \alpha) = \begin{cases} fuzzy\_equal(x, t, \alpha), & x > t, \\ 1, & otherwise. \end{cases} \tag{18}$$

$$fuzzy\_high(x, t, \alpha) = \begin{cases} fuzzy\_equal(x, t, \alpha), & x < t, \\ 1, & otherwise. \end{cases} \tag{19}$$

The parameter α in formulas (18) and (19) holds the same meaning in formula (2).

Table 2
Relationship between emotions and modulators. (H = high, L = low, M = medium, EL = extremely low, EH = extremely high and U = undefined).

	Angry	Fear	Happy	Sad
Activation	H	H	H	L
Resolution	L	L	L	H
Securing threshold	H	L	H	L
Selection threshold	L	H	H	L
Pleasure	L	L	H	L

Table 3
Current modulator levels.

Modulator	Value
Activation	0.3441
Resolution	0.6532
Securing threshold	0.5762
Selection threshold	0.2504
Pleasure	0.1783

Table 4
Current emotional intensities.

Emotion	Intensity
Angry	0.4808
Fear	0.2426
Happy	0.0919
Sad	0.7214

After calculating the intensities of all the emotions, the dominant emotion $\widehat{E}$ with greatest intensity is selected and can be processed further, such as emotional expression etc.

For instance, given the relationship of emotions and modulators (Table 2), we firstly calculate intensities of each emotions according to current modulator levels (Table 3). For example, assuming all the W_m are equivalent (all equals to 1/5) then the intensity of Anger could be calculated as,

$I(Anger) = 0.2 * P(0.3441,H) + 0.2 * P(0.6532,L) + 0.2 * P(0.5762,H) + 0.2 * P(0.2504,L), 0.2 * P(0.1783,L) = 0.4808$

Then Sad is selected as the dominant emotion, since it has the highest intensity 0.7214 (Table 4).

5. Simulation results

In order to test the dynamics of proposed model, a number of experiments (under different parameter settings) have been performed. As shown in Table 5, each experiment uses different parameter settings related to resources, such as water or food amount, to simulate different environments. However, all the avatars in all the experiments share the same parameters of emotional model (Table 6), such as initial modulator values and the target range of each demand. That means all the experimental results presented here are caused by different environments and the dynamics of the affective model itself, rather than a set of carefully tuned parameters of emotional model.

Table 5
Values of variables related to environment.

No.	Avatar type A amount	Avatar type B amount	Water amount	Food amount
1	10	10	10	10
2	10	10	20	20
3	10	10	30	30
4	20	20	10	10
5	20	20	20	20
6	20	20	30	30
7	30	30	10	10
8	30	30	20	20
9	30	30	30	30

Table 6
Values of variables related to demands and modulators.

Variable	Fixed value	Initial value
Activation	NA	0.7
Resolution	NA	0.6
Securing threshold	NA	0.7
Selection threshold	NA	0.8
Energy level	NA	0.9
Minimum energy level	0.70	NA
Maximum energy level	1.00	NA
Water level	NA	0.95
Minimum water level	0.75	NA
Maximum water level	1.00	NA
Integrity level	NA	0.95
Minimum integrity level	0.90	NA
Maximum integrity level	1.00	NA
Affiliation level	NA	0.30
Minimum affiliation level	0.50	NA
Maximum affiliation level	1.00	NA
Certainty level	NA	0.40
Minimum certainty level	0.75	NA
Maximum certainty level	1.00	NA
Competence level	NA	0.80
Minimum competence level	0.85	NA
Maximum competence level	1.00	NA

Two types of perspectives are addressed:

- General view (Section 5.1), which focuses on the average emotional levels under different circumstances. The basic idea here is that, if the emotions in our proposed model emerge from the system, it should present some reasonable trends that are not predefined in the model. For example, when there are more resources, like food or water, in the environment, avatars would probably feel happier. According to Fig. 9, we successfully observe this trend, which is not hard coded in the model but fits our common sense.
- Individual view (Section 5.2), which presents changes of internal states, including demand satisfactions, modulator levels and feeling levels in detail, for each of six randomly selected avatars. We found that the dynamics of emotional changes become more complex as the resources getting more abundant. Further more, we observe some different phases of emotional changes of these avatars, predicted by Lewis's dynamical theory of emotions.

5.1. Emotions emerge from the interaction with the environment

In this case, we firstly calculated the average emotional levels of avatars during experiments with different resource allocations listed in Table 5. Then we compared the average emotional levels with different environmental settings. Fig. 9 consists of nine bar graphs, each of which shows the comparison of average emotional levels during two experiments listed in Table 5. These bar graphs are arranged in three rows carefully, that all the graphs in the same row share the same avatar numbers but with different water and food amount. The arrangement of Fig. 10 is similar to Fig. 9; graphs in the same row share the same water and food amount, but with different avatar numbers. Then we found two non-trivial trends as follows:

- Avatars living in an environment with more water and food, in which case water and energy demands are more easily satisfied, tend to experience more happiness and less sadness (Fig. 9).
- Avatars living in an environment with larger avatar numbers, in which case affiliation demand is more likely to be contented, tend to be happier and and feel less sad (Fig. 10).

It is important to note that both two trends are not predefined in our emotional model and they fit our common sense quite well. We argue that they are the evidences that emotions in our proposed model emerge from the interaction between avatar and the environment where it lives, since emotions are affected by resource allocations in the environment, and this relationship is not explicitly defined in our model.

5.2. Different phases of emotional dynamics

Since it is difficult to observe the dynamics of emotions from the general perspective, six avatars are selected, almost randomly, to verify the dynamics of our proposed model under different circumstances. Fig. 11 shows the internal changes of two avatars in the environment with insufficient resources; Figs. 12 and 13 show emotional dynamics in the environments with sufficient and plentiful resources respectively. As can be seen from comparison of these three figures, the emotional changes become more complex with the amount of resources increase. This may be explained as in an environment short of resources (Fig. 11), avatars tend to gather around food and water for survival. Hence the emotional variations are very constraint in this case. However, if avatars live in an environment full of food and water (Fig. 13), they can explore the world more freely and do other interesting stuff like meeting friends or fighting with enemies, that causes more dynamics of emotions.

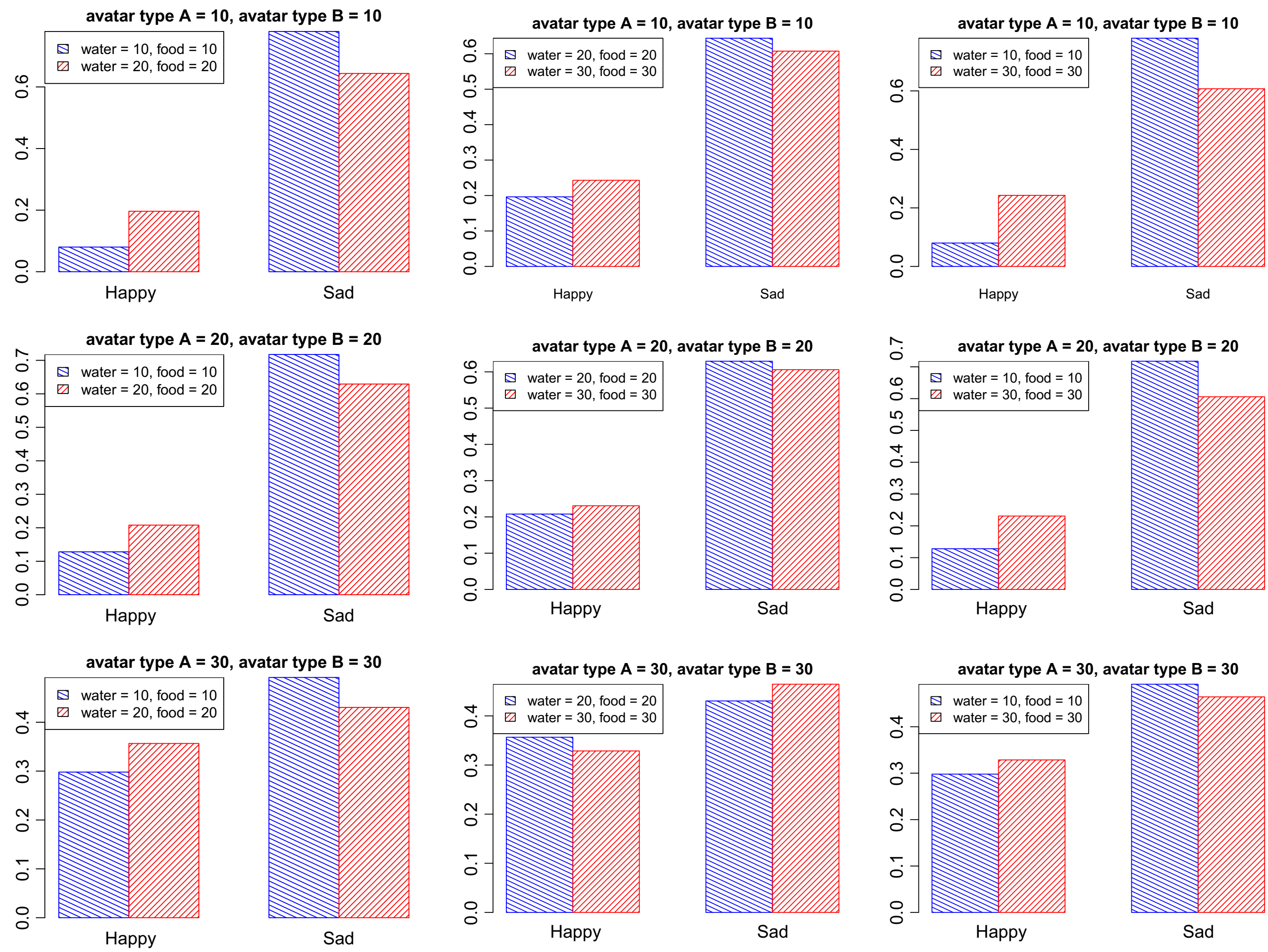

Fig. 9. Average emotions change with the variation of food and water.

In addition, when we study more carefully, we found some hints of different phases as suggested by Lewis's dynamical theory of emotions. Take avatar with $id = 23$ (left lower corner of Fig. 13) as an example, emotional levels change dramatically in $mind\ cycle = 3000$, which may experience self-amplification phases, since small deviations accumulated during previous stages are rapidly amplified. Before $mind\ cycle = 3000$, there are small and frequently variations, which may stand for trigger phases. Within the trigger stage, the orderliness is lost by perturbation from the environment and the system becomes sensitive to the environment; while after $mind\ cycle = 3000$, the system might undergo self-stabilization phases as negative feedback gradually takes control of the system dynamics and the variations of emotional levels decrease. During this stage the avatar feel more sad than happy. When we check its demand satisfactions (left upper corner of Fig. 13), we got the reason is that its affiliation level is critical low during that period. Two other phase transitions can also be observed when *mind cycle* falls between 6000 to 7500. The emotional changes during this period can also be explained by the variations of demand satisfactions (left upper corner of Fig. 13). During this period, the avatar experiences happiness as affiliation and water demands are satisfied and then the happiness level decreases as the avatar runs out of energy.

6. Discussion

6.1. Conclusion

In this paper, a formal model for Dörner's PSI theory has been introduced. The affective model and a simple virtual world for simulation have been constructed.

Simulation experiments have been performed for different situations, environments with insufficient, adequate and plentiful resources separately. However, we fixed the parameters of emotional model itself, which eliminates the possibility of distorting simulation results by means of turning these parameters. The experimental results are then analyzed from two perspectives, general view and individual view in detail. Two non-trivial trends are discovered by comparison of average emotional levels under different circumstances: avatars experience more happiness when living in a world with more food and water and avatars feel happier as there are more friends exist in the

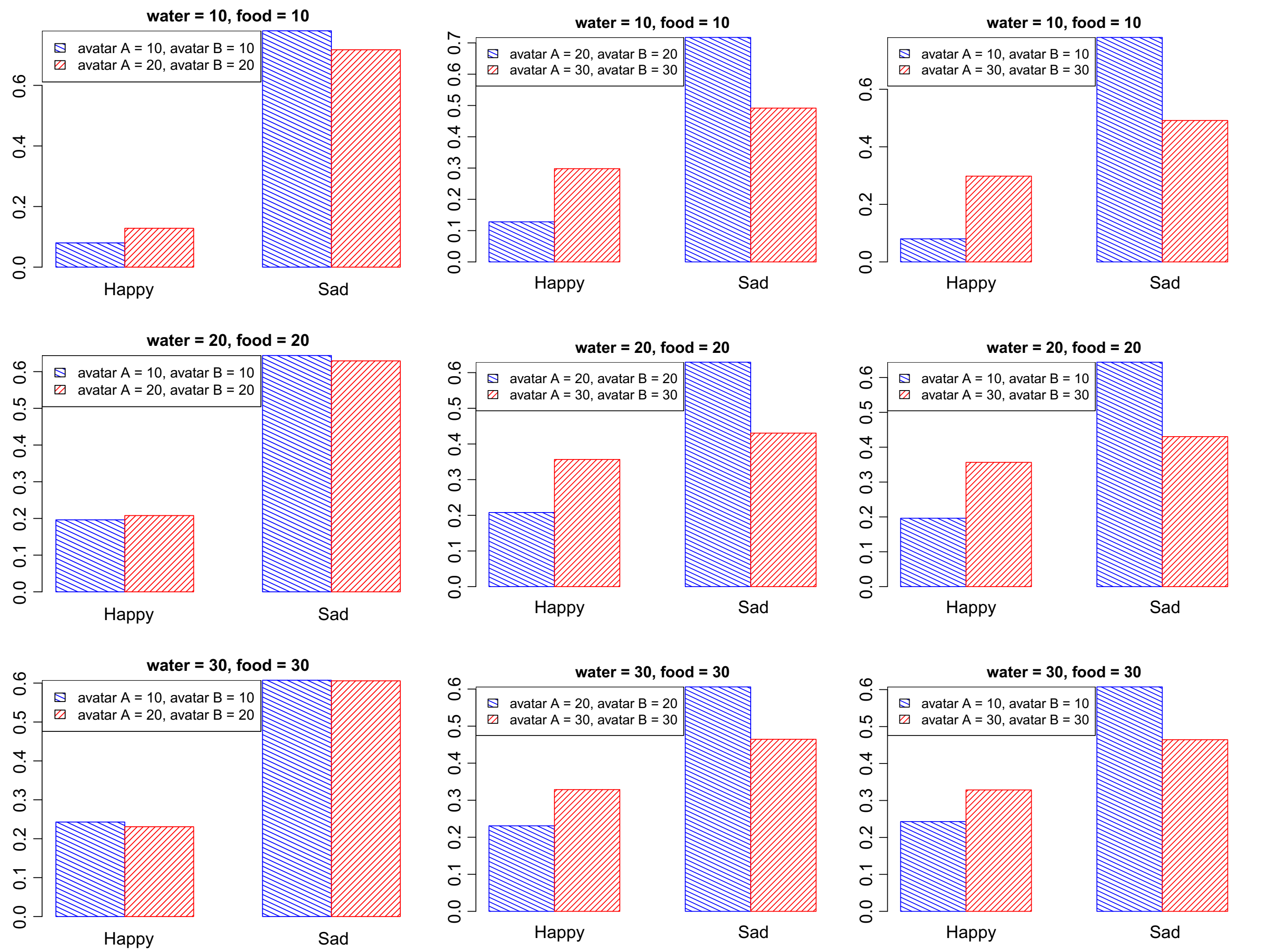

Fig. 10. Average emotions change with the variation of avatar numbers.

environment. Both two patterns are reasonable and fit our common sense quite well. Moreover, they are not predefined by the emotional model. Thus, they may serve as evidences that emotions in our proposed model emerge from the dynamics of interactions between the avatars and the environment.

Since the variations of average emotions do not show the dynamics of emotions directly, we selected six avatars, almost randomly, under different situations to study their internal changes in detail. The experimental results seem quite promising as we successfully found several hints of phases transitions as suggested by Lewis, including trigger phase, self-amplification and self-stabilization phases. In addition, these phase changes comply with the variations of demand satisfactions, i.e., the happiness level increase as demands being satisfied and decreases when demands are not properly contented. Another interesting pattern is also discovered in our analysis, the emotional changes become more complicated as the amount of resources in the environment increase.

These simulation results show our computational model inspired by Dörner's PSI theory is a quite promising approach of emotion modeling, as three essential features are presented:

- Emotions emerge from the dynamics of the system automatically, rather than derived by a set of predefined appraisal rules.
- Emotional changes experience critical phase transitions, such as trigger, self-amplification and self-stabilization stages.
- Emotional phase transitions comply with the dynamics of the environment, i.e., both emotion and emotional changes are grounded to the environment.

6.2. Comparison

The ACT-R model (Anderson, 1996, 2000; Lebiere & Anderson, 2008) is a hybrid production-system of human cognition. At the symbolic level, ACT-R is defined in terms of declarative memory of long-term facts, and procedure memory holding general production rules. It is a goal-directed system with a stack of goals, onto which new goals

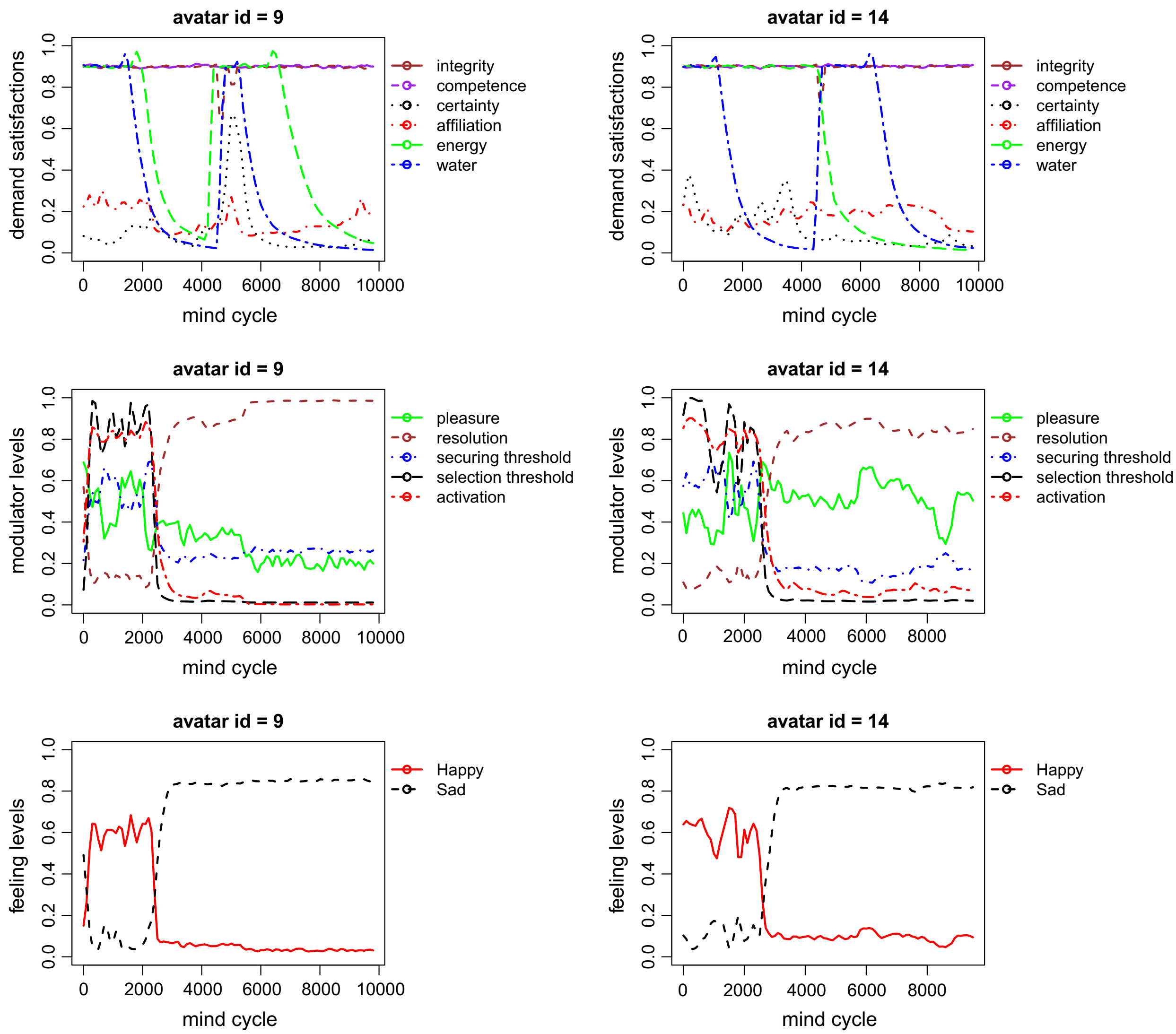

Fig. 11. Dynamics of two avatars (avatar type A = 10, avatar type B = 10, food = 10, water = 10).

can be pushed and satisfied goals popped. It is also an activation-based system in which the behavior at symbolic level is controlled by associated real-valued parameters. These parameters are learned by Bayesian learning mechanism to reflect the system's environment (Lebiere, 1999). ACT-R contains various mechanisms for learning new rules and sophisticated probabilistic equations for updating activation levels associated with items of knowledge.

The CLARION model (Sun & Peterson, 1996, 1998; Sun, Merrill, & Peterson, 1998) was firstly proposed as skill learning model, which adopts a bottom-up approach toward low-level skill learning, that is procedure knowledge develops first and then declarative knowledge develops. However, CLARION has been greatly improved and become a domain generic computational cognitive model (Sun, 2007; Sun & Naveh, 2004). Its capability of modeling consciousness was also discussed (Coward & Sun, 2004). CLARION is mainly made up of four subsystems, action-centered subsystem (the ACS), the non-action-centered subsystem (the NACS), the motivational subsystem (the MS), and the meta-cognition subsystem (the MCS) (Sun, 2007).

ACT-R, CLARION and our model are all goal-directed architectures. Further more, both CLARION and our model take high-level and low-level into consideration during action decision making. However, they achieve this in quite different approaches. In CLARION, the combination of high-level and low-level decision making is performed explicitly, by combining Q-values of actions in the bottom level and explicit symbolic rules in the top level. In our computational model, decision makings in different levels are more implicit. The dominant goal is firstly selected by competition of demands in the low level, and then a bunch of candidate actions are obtained by action planner in the higher level with a number of symbolic rules.

Another distinction among these three architectures is how to modulate the system behavior. In ACT-R a number of real-valued quantities learned by Bayesian principles are used to control the performance at symbolic level; in

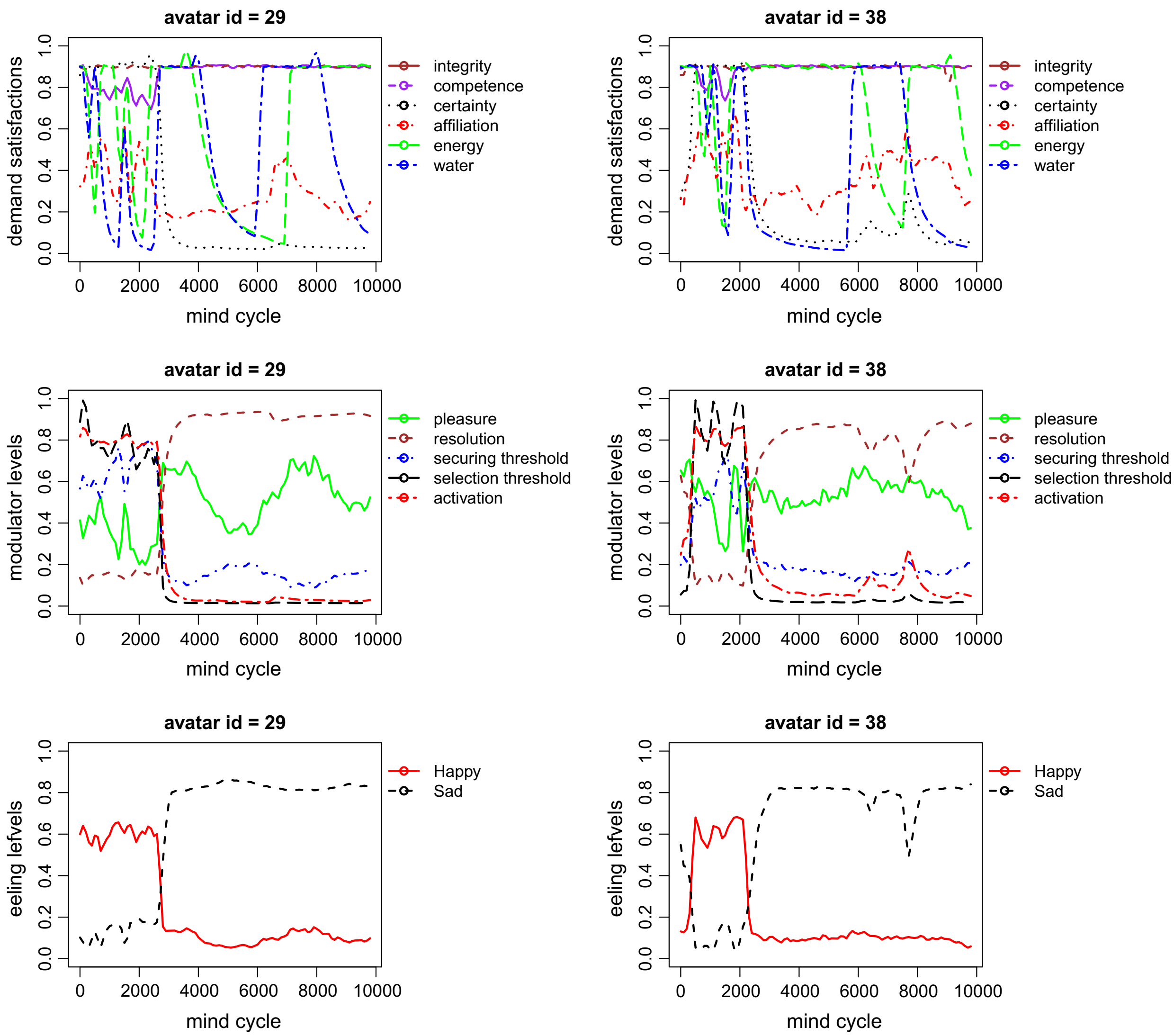

Fig. 12. Dynamics of two avatars (avatar type A = 20, avatar type B = 20, food = 20, water = 20).

CLARION, an explicit meta-cognition subsystem is introduced to achieve this; while in our model a set of modulators are carefully selected, which modulate all sorts of cognitive processes, perception and action execution.

Compared with ACT-R and CLARION, the most distinctive feature of our model is that it lacks a decent learning mechanism, but it puts heavy emphasize on explaining how different emotions emerge from the dynamics of a complex cognitive system, how emotions have impact on cognitive processes, perception and action execution via modulations, and how these modulators could be closely related by non-linear functions.

6.3. Future work

Many improvements could still be made to the model. For example, target ranges of demands are currently fixed in the initial implementation. These could be made dynamic, by means of learning form real time appraisal processes. Another improvement could be implementing more emotions rather than just happiness and sadness, which requires a more complex virtual world. Since emotions of our proposed model emerge from the dynamics of the environment, it is quite impossible to model other emotions like anger, fear etc., in a too simplified game world, as the one presented in this paper. A final extension would be introducing more complex interaction between emotions and cognitive process such as planning, which also relies on a more rich and colorful game world. At the same time of writing this paper, we are also busy with incorporating this computational model in a minecraft like game (see also http://www.minecraft.net/). Similar to minecraft, our game world on going is also a virtual world full of building blocks that could be used by players or NPCs (non-player characters) to create anything needed. The affective model proposed in this paper would be used to control NPCs in the game, which would help human players improving their experiences of playing the game. Actually some other emotion models have been applied to autonomous NPCs as described by Lim, Dias, Aylett, and Paiva (2010).

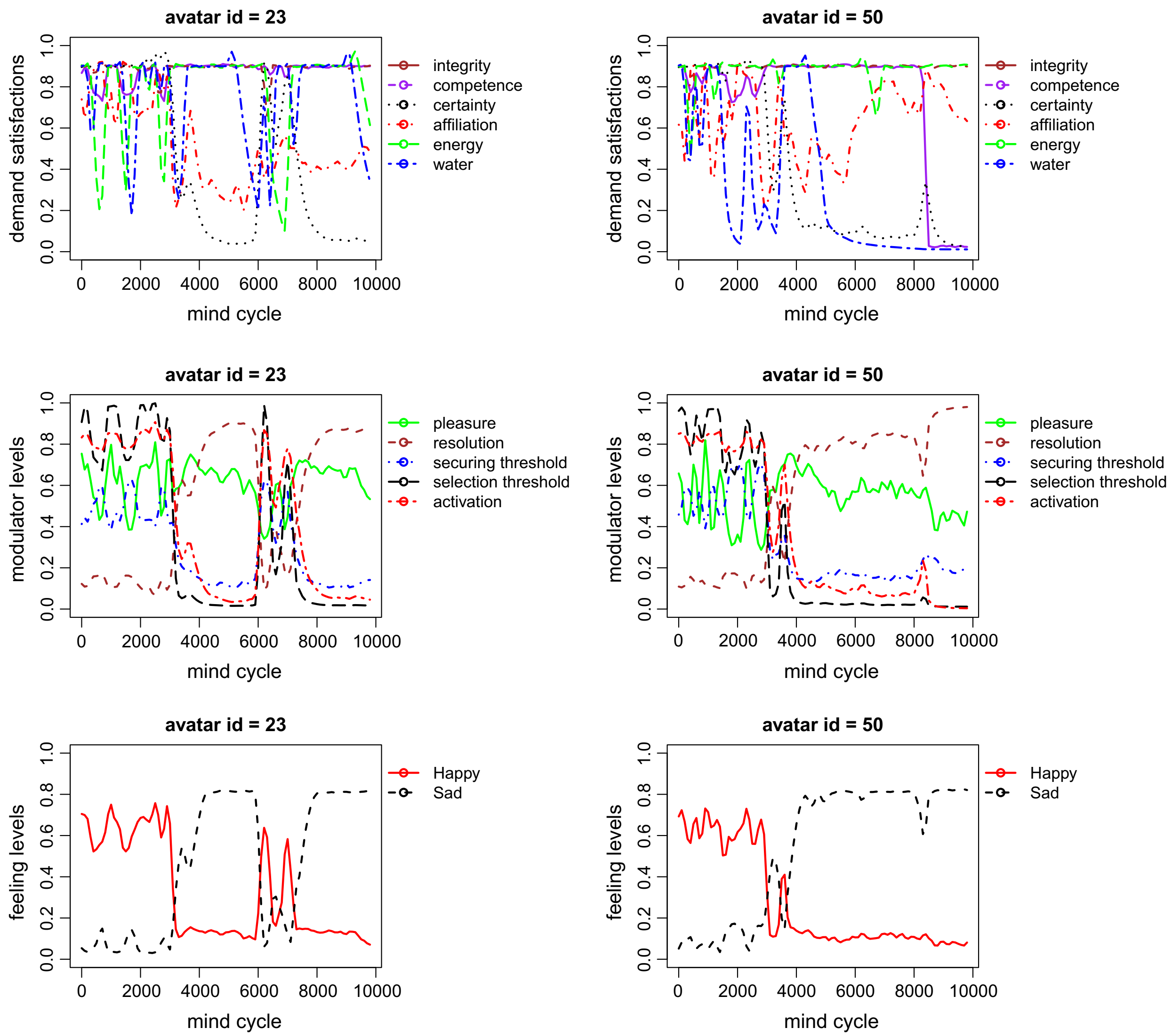

Fig. 13. Dynamics of two avatars (avatar type A = 30, avatar type B = 30, food = 30, water = 30).

However, we will not constrain ourselves only in the game industry. As soon as the model has been verified and adapted in the game world, we would like to explore the possibilities to apply it in the real world, which is, of course, much more complicated than the game world, that is applying this model to a robot in the real world, that can communicate affectively with humans in a more natural way. A more complex environment is of both challenge and chance for our emotional model. Because in our model, emotions are heavily coupled with the environment, there would be chances to observe more emotions and more interesting dynamics within a more complex and dynamic environment.

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