Modeling Adaptive Dynamical Systems to Analyze Eating Regulation Disorders

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To analyze the disorders of their patients, psychotherapists often have to get insight in adaptive dynamical systems. Analysis of dynamical systems usually is performed using mathematical techniques. Such an analysis is not precisely the type of reasoning performed in psychotherapy practice. In this article, it is shown how practical reasoning about dynamic properties of adaptive dynamical systems within psychotherapy can be described using a high-level logical language to describe dynamics. Using this language, an executable model has been developed of the dynamics of eating regulation disorders. Based on this model, a number of simulation traces have been generated, both for well-functioning situations and for different types of malfunctioning situations that correspond to the first phase of well-known disorders such as anorexia (nervosa), obesitas, and bulimia. Next, it is shown how such traces can be automatically analyzed against a number of dynamic properties.

Keywords: Adaptive dynamical systems, eating regulation disorders, psychotherapy, simulation and analysis

1. Introduction

Within the context of psychotherapy, often types of human behavior and development are addressed that are highly complex, dynamic, and adaptive. Recently, it has been suggested that the dynamical systems theory (DST) [1] could be an adequate tool for psychotherapists to describe and analyze such behaviors (e.g., [2-5]). However, application of the DST approach in the practice of psychotherapy is not at all straightforward, and much remains to be done. A therapist's reasoning usually is performed in an informal, intuitive, partly conscious manner. Explanation of (at least parts of) this reasoning may take place in a qualitative, logical manner. In contrast, DST requires quantitative mathematical modeling, and analysis of dynamic properties is based on quantitative techniques from mathematics. This contrast between *qualitative, logical* and *quantitative, mathematical* makes it very difficult, if not impossible, to use the DST approach in this domain. As an alternative, this article shows how hybrid modeling techniques (i.e., combining qualitative and quantitative modeling concepts)

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are better suited to adequately describe the manner in which reasoning about such an adaptive dynamical system in therapy practice takes place or can take place in a systematic manner.

Within the areas of computer science and artificial intelligence, recently alternative techniques have been developed to analyze the dynamics of phenomena using logical means. Examples are dynamic and temporal logic, as well as event and situation calculus (e.g., [6]). These logical techniques allow us to consider and relate states of a process at different points in time. The form of these relations can cover qualitative aspects but also quantitative aspects.

The objective of this article is twofold. First, it introduces an alternative approach for the analysis and formalization of adaptive dynamical systems. Second, it illustrates the usefulness of this approach in a particular domain of psychotherapy practice: the first phase of eating regulation disorders (e.g., [7, 8]). For the second objective, a model will be developed that is inspired by a model by Delfos [9]. In that paper, an adaptive dynamical model that describes normal functioning of eating regulation under varying metabolism levels is used as a basis for the classification of eating regulation disorders, as well as diagnosis and treatment within a therapy. Reasoning about the dynamics of this model (and disturbances of them) is performed in an intuitive, conceptual, but informal manner. This article shows how the model by Delfos [9] can be formalized in our modeling approach.

In particular, in section 2, the approach for modeling adaptive dynamical systems is briefly introduced. Section 3 summarizes the main ideas of the model for eating regulation by Delfos [9]. In section 4, this model is formalized in a high-level executable format. Based on the formalized model, section 5 shows some example simulations, both for well-functioning situations and for different types of malfunctioning situations that correspond to the first phase of well-known disorders such as anorexia (nervosa), obesitas, and bulimia. In section 6, as part of our analysis, a number of relevant dynamic properties of the dynamical system are identified and formalized at different levels of aggregation: both for the regulation as a whole and for separate parts of the adaptive system. In section 7, it is shown how these dynamic properties logically relate to each other (i.e., which properties at the lower level of aggregation together imply given properties at the higher level). Such logical relationships are especially important for the diagnosis of a malfunctioning system. Moreover, in section 8, it is shown how these dynamic properties can be automatically checked (using a software environment that has been developed) against a number of simulation traces. In section 9, it is explained in detail how the modeling approach used in this article relates to the DST. Section 10 concludes the article with a discussion.

2. Modeling Approach

The domain of reasoning about dynamical systems in psychotherapy requires an abstract modeling form that shows the essential dynamic properties. As dynamic properties of such a dynamical system can be complex, a high-level language is needed to characterize them. To this end, the *Temporal Trace Language* (TTL) is used as a tool; for previous applications of this language to the analysis of (cognitive) processes, see, for example, Jonker and Treur [10]. Using this language, dynamic properties can be expressed in an informal, a semiformal, or a formal format. The language allows us to explicitly refer to (real) time and to developments of processes over time. Moreover, to perform simulations, models are desired that can be formalized and are computationally easy to handle. These executable models are based on the so-called LEADSTO format, which is defined as a sublanguage of TTL; for a previous application of this format for the simulation of cognitive processes, see Jonker, Treur, and Wijngaards [11]. TTL is briefly defined as follows.

A *state ontology* is a specification (in order-sorted logic) of a vocabulary to describe a state of a process. A state for ontology Ont is an assignment of truth-values true or false to the set At(Ont) of ground atoms expressed in terms of Ont. The *set of all possible states* for state ontology Ont is denoted by STATES(Ont). The set of *state properties* STATPROP(Ont) for state ontology Ont is the set of all propositions over ground atoms from At(Ont). A fixed *time frame* T is assumed, which is linearly ordered (e.g., natural or real numbers). A *trace* γ over a state ontology Ont and time frame T is a mapping $\gamma : T \rightarrow \mathrm{STATES(Ont)}$, that is, a sequence of states γ_t ($t \in T$) in STATES(Ont). The set of all traces over state ontology Ont is denoted by TRACES(Ont). The set of *dynamic properties* DYNPROP(Ont) is the set of temporal statements that can be formulated with respect to traces based on the state ontology Ont in the following manner.

These states can be related to state properties via the formally defined satisfaction relation $\models$, comparable to the Holds-predicate in situation calculus (cf. [6]): state(γ, t) $\models$ p denotes that state property p holds in trace γ at time t. Based on these statements, dynamic properties can be formulated, using quantifiers over time and the usual first-order logical connectives $\neg$ (not), & (and), $\vee$ (or), $\Rightarrow$ (implies), $\forall$ (for all), and $\exists$ (there exists); to be more formal: formulas are in a sorted first-order predicate logic with sorts T for time points, Traces for traces, and F for state formulas.

To model basic mechanisms of a process at a lower aggregation level, direct temporal dependencies between two state properties, the simpler LEADSTO format is used. This executable format can be used for simulation and is defined as follows. Let α and β be state properties. In LEADSTO specifications, the notation $\alpha \twoheadrightarrow_{e,f,g,h} \beta$ means the following:

If state property α holds for a certain time interval with duration g, then after some delay (between e and f), state property β will hold for a certain time interval h.

For a more formal definition of the LEADSTO format, see Bosse et al. [12].

3. Eating Regulation

To illustrate the applicability of the approach for modeling adaptive dynamical systems, the remainder of this article focuses on a specific domain: eating regulation disorders. Psychologist Martine Delfos [9] describes an analysis and treatment of eating regulation disorders from the perspective of predisposition. The main assumption behind her theory is that physical predisposition is an important factor in the development of eating regulation disorders, rather than, for example, striving for beauty. Based on this theory, three types of aspects can be distinguished in the treatment of eating regulation disorders: biological aspects, psychological/behavioral aspects, and therapeutic aspects.

Point of departure of the therapeutic intervention in Delfos [9, chap. 5] is the biological mechanism: the so-called *adipostat*, a kind of thermostat for weight or fat. The idea is that the eating regulation disorder is primarily caused by biological problems. For example, in the case of anorexia, the signal "stop eating" might come too early with respect to the amount of energy deployed. After noticing such problems, the subject may add a psychological component by changing his or her behavior: psychological/behavioral factors play a role mainly in the subject's response to this biological problem or the subject's response to the response of others (e.g., parents) to the problem. Within a therapy as described in Delfos [9, chap. 5], in the first place, the biological problem is addressed. The biological problem is that in one way or the other, the adipostat does not function properly: it does not adapt the food intake stimulus to changing circumstances with respect to the need of energy (given by metabolism and activities). Recently, neural mechanisms in the brain have been found for the adipostat (e.g., [13]). When the adipostat malfunctions, these neural mechanisms have to be corrected. This can be done by therapy, which takes the form of training the brain. By this training, the improper functioning of the adaptation process in the adipostat is corrected. Training is done by learning to pay more explicit attention (of the client) to the balance between food and activity (per day), thus developing a more accurate monitoring of what the body takes in and what it needs. By checking weight every day, feedback is obtained on the (estimated) balance between intake and need.

In the next sections, part of this theory will be formalized, using the approach based on TTL and LEADSTO. The focus will be on the biological aspects. Thus, the physical mechanisms that lead to deviations in eating behavior are modeled. Having such a model in mainly qualitative terms will allow the psychotherapist to reason about dynamic processes in an intuitive way, which is nevertheless more systematic than the informal type of reasoning that is used traditionally.

4. Local Properties

Local properties are dynamic properties of the basic mechanisms in the dynamical model. Based on these properties, the global properties of the system emerge; they together entail these global properties. Local properties are specified in the executable LEADSTO format; for simplicity, below, the parameters e, f, g, and h have been left out (their values are discussed in section 5).

This section presents an adaptive dynamical model that describes the biological aspects of eating regulation under varying metabolism levels in terms of local dynamic properties. As mentioned in the previous section, this model is inspired by Delfos [9]. An overall picture of the model can be found in Figure 1. As the figure shows, in eating regulation, three types of processes are distinguished (*sensory processes*, *adaptation*, and *action generation*) that together influence the state of the body. The arrows denote the fact that the output of one process serves as input for another process.

The local properties that describe the dynamics of the model are given below. The first two (*action generation*; see Fig. 1) properties characterize when a stimulus to eat is generated, based on an internal eat norm N that is maintained.

LP1 (eat stimulus). The first local property LP1 expresses that an eat norm N and an intermediate amount eaten E less than this norm together lead to an eat stimulus. Formalization:

intermediate_amount_eaten(E) and eat_norm(N) and $E < N \rightarrow$ stimulus(eat)

Note that is it assumed that the initial value of the eat norm N is biologically determined.

LP2 (not-eat stimulus). Local property LP2 expresses that an eat norm N and an intermediate amount eaten E higher than this norm together lead to a not-eat stimulus. Formalization:

intermediate_amount_eaten(E) and eat_norm(N) and $E \geq N \rightarrow$ stimulus(do_not_eat)

The properties LP3, LP4, LP5, and LP6 characterize the effect of eating (on *body state*); it is assumed that the outcomes on amount eaten are taken by *sensory processes*.

LP3 (increase of amount eaten). Local property LP3 expresses how an eat stimulus increases an intermediate amount eaten by additional energy d (the energy value of what is eaten). Formalization:

intermediate_amount_eaten(E) and stimulus(eat) $\rightarrow$ intermediate_amount_eaten(E + d)

LP4 (stabilizing amount eaten). Local property LP4 expresses how a not-eat stimulus keeps the intermediate amount eaten the same. Formalization:

intermediate_amount_eaten(E) and stimulus(do_not_eat) $\rightarrow$ intermediate_amount_eaten(E)

LP5 (day amount eaten). Local property LP5 expresses

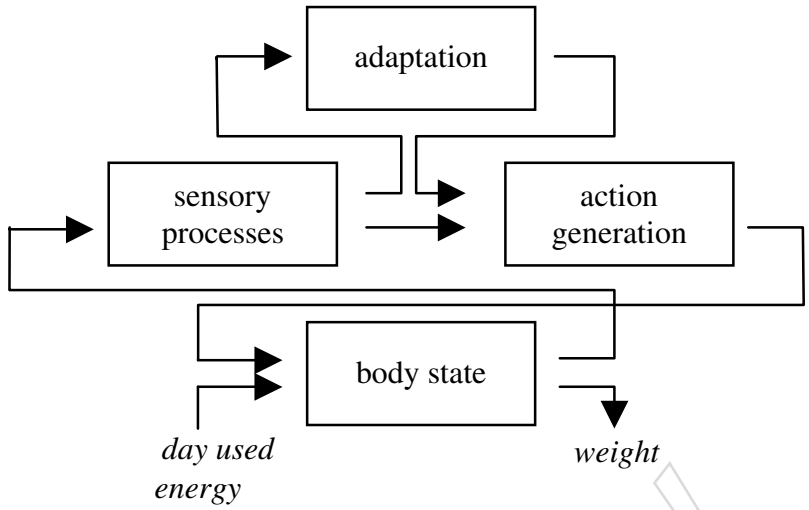

Figure 1. Overview of the executable model

that the day amount eaten is the intermediate amount eaten at the end of the day. Formalization:

intermediate_amount_eaten(E) and time(24) → day_amount_eaten(E)

Here, time counts the hours from 1 to 24 during the day.

LP6 (weight through balance of amount eaten and energy used). Local property LP6 expresses a simple mechanism of how weight is affected by the day balance of the amount eaten and energy used. Here, γ is a fraction that specifies how energy leads to weight kilograms. Formalization:

day_amount_eaten(E1) and day_used_energy(E2) and weight(W) → weight(W + γ * (E1 – E2))

The last local property characterizes *adaptation*: how the eat norm N is adapted to the day used energy.

LP7 (adaptation of amount to be eaten). Local property LP7 expresses a simple (logistic) mechanism for the adaptation of the eat norm based on the day amount of energy used. Here, α is the adaptation speed, and β is the fraction of E that is the limit of the adaptation; normally, $\beta = 1$. Formalization:

day_used_energy(E) and eat_norm(N) and time(24) → eat_norm(N + α * N * (1 – N/βE))

Note that different types of eating regulation disorders can be modeled by varying the values for the parameters α and β. By choosing a high value for α, the adaptation of the eat norm to the energy use is made very sensitive, as is the case with bulimia. If a lower value for α is chosen, the adaptation proceeds more gradually. The value of β determines the precision of the adaptation. If β is exactly 1, then the eat norm is adapted perfectly to the amount of energy used. If $\beta < 1$, the new eat norm does not become high enough (as with anorexia), and if $\beta > 1$, the eat norm becomes too high (as with obesitas). See the next section for details.

5. Simulation Examples

A special software environment has been created to enable the simulation of executable models [12]. Based on an input consisting of dynamic properties in the LEADSTO format, the software environment generates simulation traces. Examples of such traces can be seen in Figures 2, 4, 5, and 6. Here, time is on the horizontal axis, and the state properties are on the vertical axis. A dark box on top of the line indicates that the property is true during that time period, and a lighter box below the line indicates that the property is false. These traces are based on all local properties presented above.

Certain parameters are the same in all three simulations. In the properties LP1 to LP5, the values (0, 0, 1, 1) have been chosen for the timing parameters e, f, g, and h. In the properties LP6 and LP7, these values are (0, 0, 1, 25); moreover, $\gamma = 0.2$ in LP6. The initial weight is always 60, the initial eat norm is always 6, and the amount of energy used on each day remains 8. Thus, we are dealing with situations where initially, the eat norm is too low with respect to the energy used and should be adapted accordingly. All simulations involve a period of 110 hours (i.e., slightly more than 4 days). In Figure 2, an example of a normal situation is shown (i.e., no eating regulation disorders are present). To simulate this, in the norm adaptation property (LP7), $\alpha = 0.75$ and $\beta = 1$; as can be seen in the figure, it takes some time before the eat norm is correctly adapted to the amount of energy used, but in the end, they are practically equal. As a consequence, the subject first undereats a little bit (6 units), causing a loss of 0.4 kilograms. However, within the next 24 hours, she starts eating more (8 units).

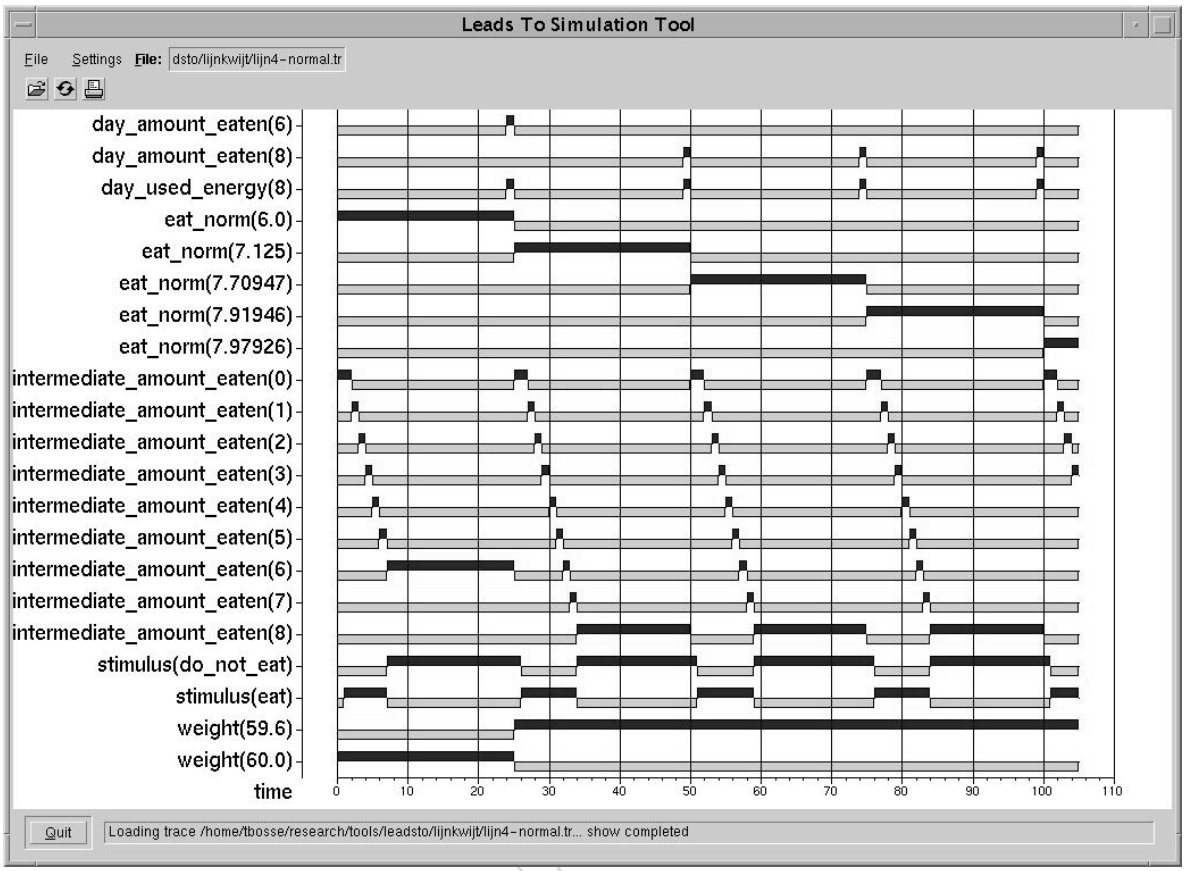

Figure 2. Simulation of a normal pattern

Subsequently, the eating pattern stabilizes, and so does the weight (at 59.6 kg).

The simulation of anorexia is based on the assumption that anorexia, in many cases, has a biological background [14]. This means that the signal "stop eating," in this simulation represented by the stimulus(do-not-eat) predicate, comes too early with respect to the amount of energy deployed. Delfos [9] proposes that as a result of this condition, there exists an unconscious phase of slight underfeeding, resulting in not gaining weight proportional to the growth and the risk of hampering growth. This first phase of anorexia, which can cover several years (especially prepuberty), consists of a discrepancy between food eaten and energy deployed at an unconscious level; the person is not consciously trying to lose weight.

In Figure 3, the anorexia process is depicted in height velocity (cm/year). The girl entered the conscious phase of her eating disorder (anorexia) when she was nearly 13 years old. It was then that she began dieting. Within a year, she was in a very bad medical condition. The height velocity, however, shows that the growth was stopped much earlier by a delay of puberty from age 10 on. After entering therapy when 14 years old, the height velocity recovered with the process of gaining weight.

Figure 4 shows a simulation of the eating pattern of a person within the first (unconscious) phase of anorexia. To simulate this, in the norm adaptation property (LP7), $\alpha = 0.75$ and $\beta = 0.95$. These settings result in an eat norm that converges a little bit to the amount of energy used, but this adaptation is not enough. The figure clearly demonstrates the consequences: the subject continuously eats an amount of food that is too low compared to what she needs. For example, in the first 24 hours, she eats only 6 units, while the amount of energy she used on that day was 8 units. Therefore, her weight drops from 60 to 59.6 to 59.4 kilograms, and this decreasing trend continues.

Figure 5 shows a simulation of the dynamics of obesitas. In this case, the parameters $\alpha = 0.75$ and $\beta = 1.2$ were chosen. This figure provides exactly the opposite pattern as Figure 4. In the case of obesitas, the simulated subject continuously eats too much and gains weight. Here, the amount of energy used again remains stable at 8 units, but the amount of food eaten increases from 6 to 10 units. As a consequence, the weight increases to 60.2 kg.

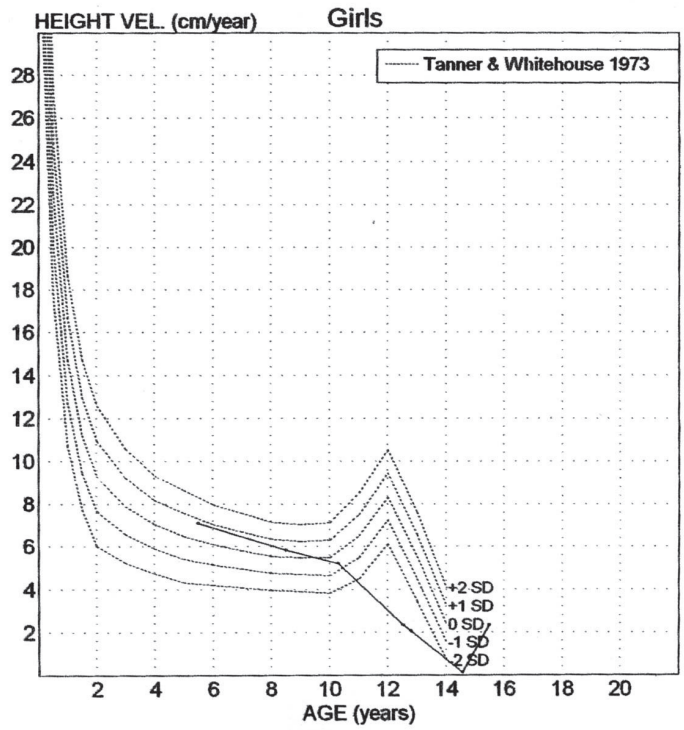

Figure 3. Height velocity pattern for anorexia

As for bulimia, there exists two kinds of situations: (1) the prephase of bulimia, in which the eating disorder exists at an unconscious level, and (2) bulimia that evolves from consciously slight underfeeding or anorectic underfeeding that results in compensating urges of excessive eating.

In Figure 6, a simulation of the eating pattern of a person in a prephase for bulimia is shown. To simulate this, in the norm adaptation property (LP7), $\alpha = 2.25$ and $\beta = 1.2$. The value of α is especially very important here because it means that the adaptation of the eat norm to energy use is too sensitive. Thus, a norm that is too low will be increased, but this increment will be too big, so that the new norm is too high. This behavior can be seen in Figure 6, where the eat norm keeps fluctuating somewhere between 6 and 12. This results in a very irregular eating pattern. Accordingly, the subject's weight fluctuates between 59 and 62. The risk of developing bulimia fully in the form as known in psychotherapy is present and will become manifest as soon as the subject starts to attempt to correct these fluctuations by conscious decisions. This further interference of more conscious cognitive aspects within the adaptive processes will be addressed in future research.

6. Analysis of Dynamic Properties of the System

Complex dynamic processes can be described at different aggregation levels, varying from the *local* level of (generating) basic mechanisms to the level of (emerging) *global* dynamic properties of a process as a whole. To analyze how such global dynamic properties relate to local properties, it is useful to distinguish *intermediate* properties. Moreover, some other (*environmental*) properties may be needed that relate the considered process to other processes that are not modeled and considered as external environment. In this section, the different types of nonlocal dynamic properties of the system are identified. For the relationships between the properties, see also Figure 7.

6.1 Environmental Properties

For the adaptive dynamical system, the amount of used energy is an exogenous variable (i.e., this comes from the *environment*). To be able to do analysis, it is convenient to consider certain simplifying assumptions on the environment. For example, to study limit behavior, a suitable assumption is that from a certain point of time, no changes occur in the used energy (EP2), or to study how the system behaves under one change, a suitable assumption is that only one change occurs in the environment (EP1). The latter type of environment may be used, for example, to study transitions occurring in subjects of around 35 years old, when the metabolism becomes slower, and hence the day amount of used energy will become lower. For each of the properties, first an informal description is given and next

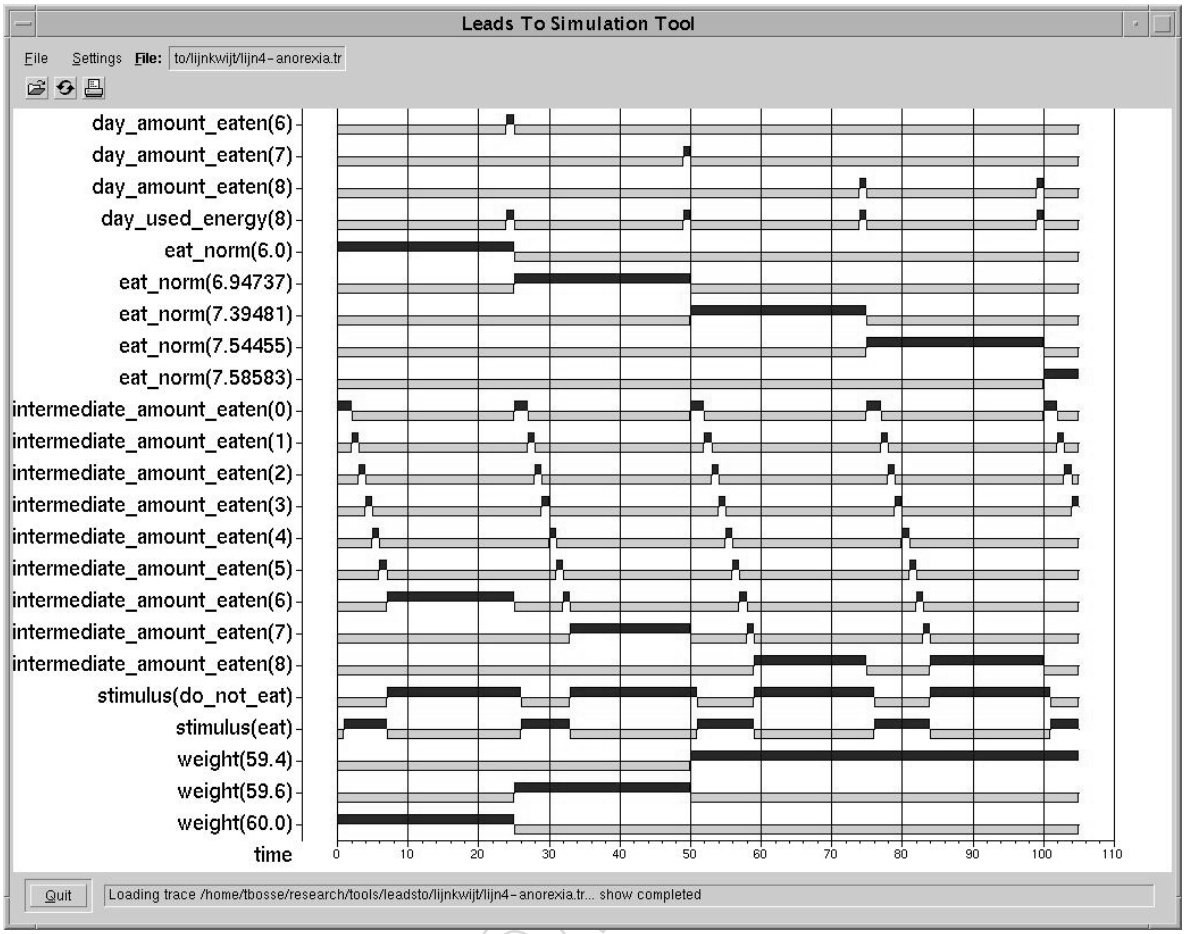

Figure 4. Simulation of the pattern of a person with anorexia

the formal description that has been used for the automated checking software; see section 8.

EP1(t1, t2, E1, E2) (Transition from one used energy E1 to other used energy E2). Property EP1 expresses that first the day amount of used energy is constant at value E1, and next it is constant at (another) value E2. Formalization:

$\forall t < t1\ \text{state}(\gamma, t) \models \text{day\_used\_energy}(E1)$
$\& \ \forall t \geq t2\ \text{state}(\gamma, t) \models \text{day\_used\_energy}(E2)$

EP2(t, E) (Constant amount of used energy E from time t). Property EP2 expresses that from a certain time point t, the day amount of used energy is constant E. Formalization:

$\forall t' \geq t\ \text{state}(\gamma, t') \models \text{day\_used\_energy}(E)$

6.2 Global Properties

Global properties (GP) are dynamic properties of the process as a whole.

GP1(W, m) (Stable weight W with margin m). Property GP1 expresses that fluctuations in weight are limited to a relative m-interval (for example, 2%) of weight W. Formalization:

$\forall t\ [\text{state}(\gamma, t) \models \text{weight}(W1) \Rightarrow -m \leq (W1 - W)/W \leq m]$

GP2(t1, t2, E1, E2, W, m) (Conditional constant weight W with margin m). Property GP2 states that GP1 holds in environments in which only one change occurs in the day amount of used energy. Formalization:

$\text{EP1}(t1, t2, E1, E2) \Rightarrow \text{GP1}(W, m)$

GP3(t, E, d, e) (Adaptation of day amount eaten). Property GP3 expresses that if the day amount of used energy is constant E after a time point t, then the day amount of food eaten will be in a relative d-interval of E. Formalization:

$\forall t\ \text{EP2}(t, E) \Rightarrow \exists t'\ t \leq t' \leq t + e\ \&\ \text{state}(\gamma, t')$
$\models \text{time}(24)\ \&$
$\forall E1\ [\text{state}(\gamma, t') \models \text{day\_amount\_eaten}(E1) \Rightarrow -d \leq$
$(E1 - E)/E \leq d]$

Note that global property GP1 describes a situation of a person with a normal eating pattern. By slightly modifying this property, also the different types of malfunctioning

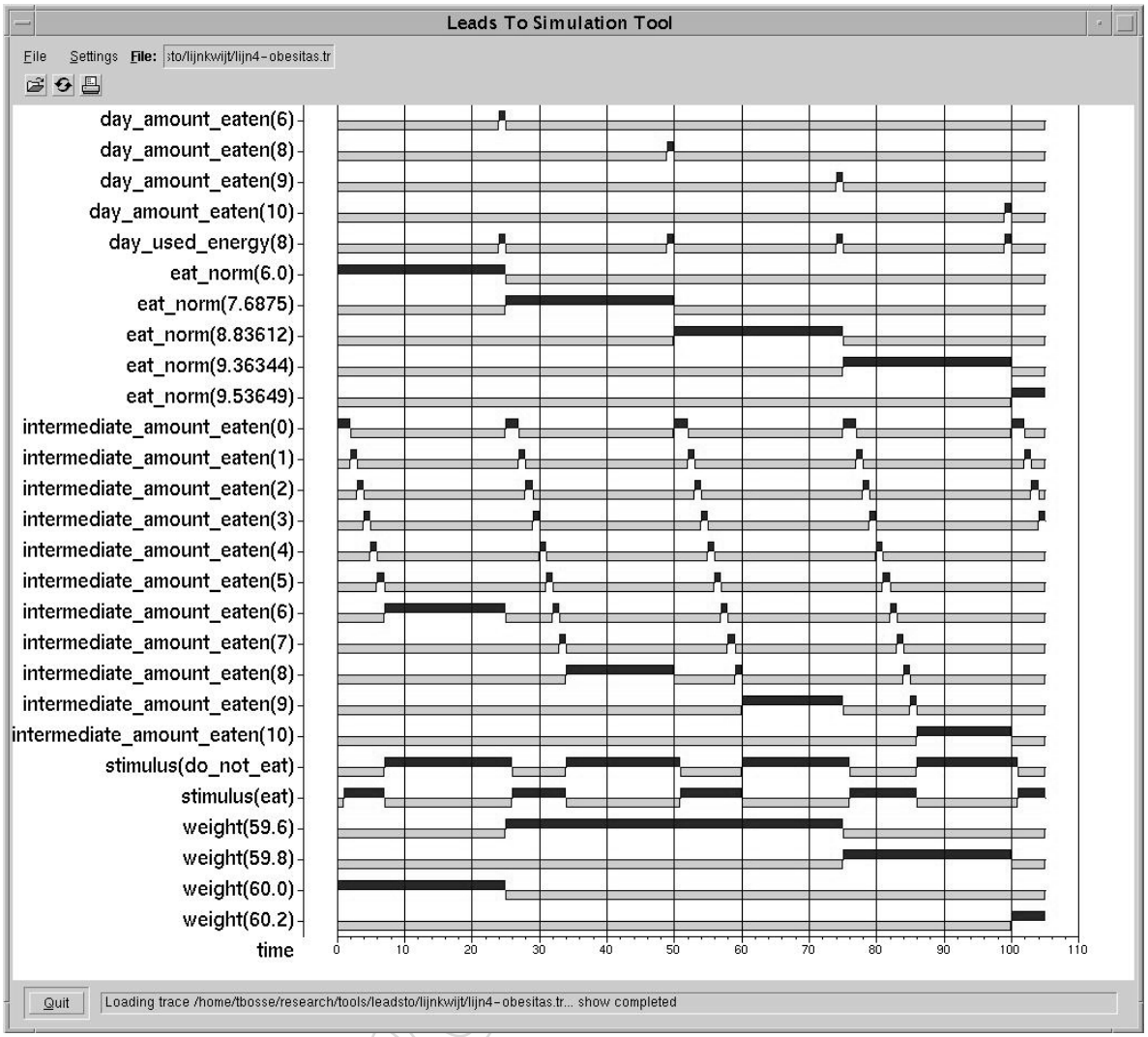

Figure 5. Simulation of the pattern of a person with obesitas

situations can be described. This results in the properties GP1a, GP1o, and GP1b for anorexia, obesitas, and bulimia, respectively.

GP1a(W, m) (Decrement of weight W with margin m). Property GP1a expresses that there is a point in time at which weight W has decreased with the relative m-interval (for example, 2%) of weight W and stays that low. Formalization:

$\exists t\ \forall t1 \geq t\ [\text{state}(\gamma, t1) \models \text{weight}(W1)$
$\Rightarrow (W1 - W)/W \leq -m]$

GP1o(W, m) (Increment of weight W with margin m). Property GP1o expresses that there is a point in time at which weight W has increased with the relative m-interval (for example, 2%) of weight W and stays that high. Formalization:

$\exists t\ \forall t1 \geq t\ [\text{state}(\gamma, t1) \models \text{weight}(W1)$
$\Rightarrow (W1 - W)/W \geq m]$

GP1b(W, m) (Periodical increment of weight W with margin m). Property GP1b expresses that for each point in time, there is a later point in time at which weight W will increase with the relative m-interval (for example, 2%) of weight W. Formalization:

$\forall t\ \exists t1 \geq t\ [\text{state}(\gamma, t1) \models \text{weight}(W1)$
$\Rightarrow (W1 - W)/W \geq m]$

6.3 Intermediate Properties

Intermediate properties are dynamic properties, normally fulfilled by parts of the dynamical system such that together, they entail the global properties.

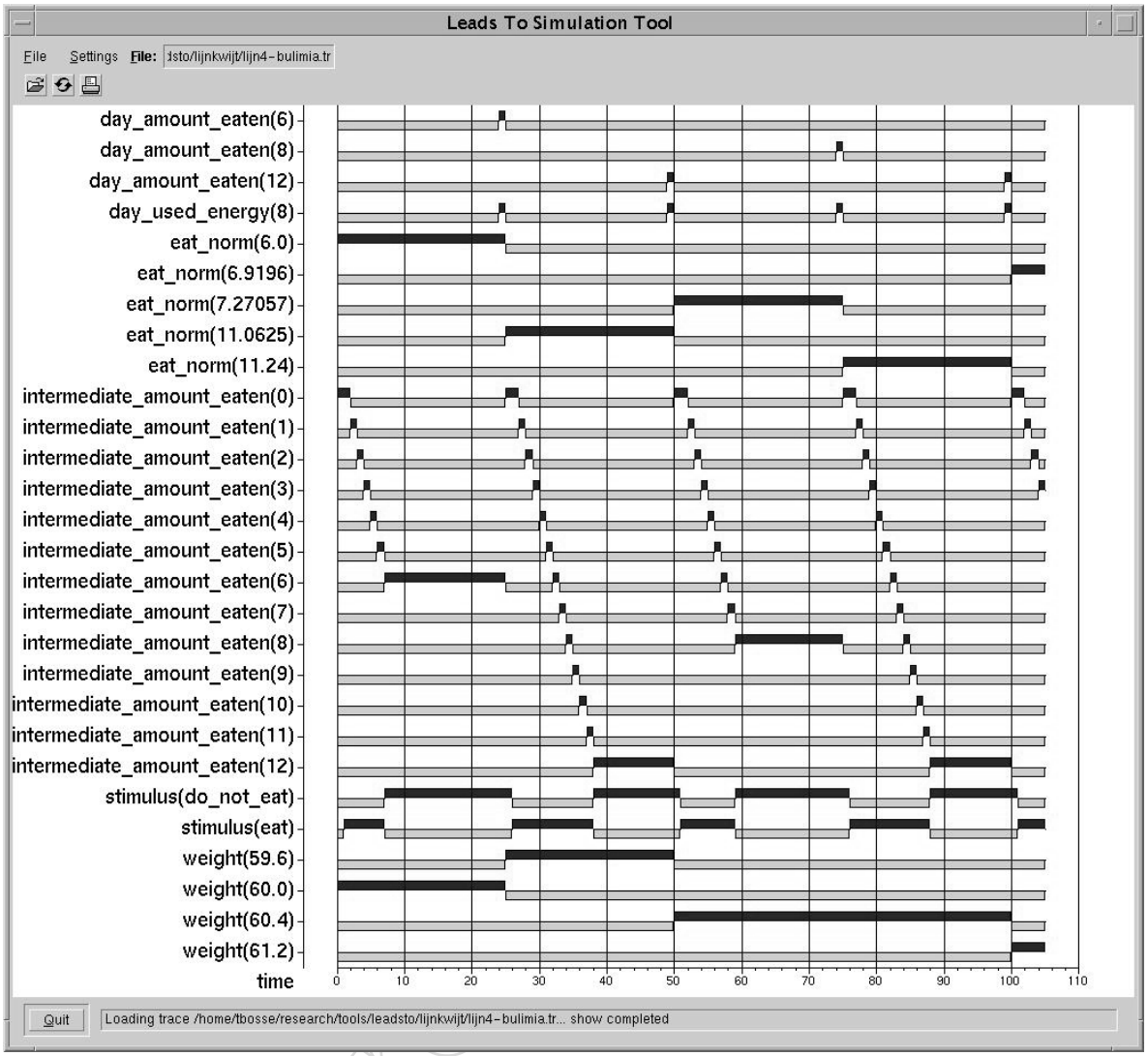

Figure 6. Simulation of the pattern of a person with bulimia

IP1(t, E, d, e) (Eat norm is adapting to used energy). Intermediate property IP1 expresses that, if the day amount of used energy is constant after time point t, then, after some time, the eat norm will be in a relative d-interval of E. Formalization:

$\forall t\ EP2(t, E) \Rightarrow \exists t'\ t \leq t' \leq t + e\ \&\ state(\gamma, t') \models time(24)$
$\&\ [state(\gamma, t') \models eat\_norm(N) \Rightarrow -d \leq (N - E)/E \leq d]$

IP2 (Eat stimuli). Intermediate property IP2 expresses how the eat norm N and the amount of food eaten together determine whether an eat stimulus occurs. It is just the conjunction of LP1 and LP2. Formalization:

LP1 & LP2

IP3 (Day eating accumulation). Intermediate property IP3 expresses how the day amount of eaten food is generated by following the eat stimuli during the day. Formalization:

LP3 & LP4 & LP5.

7. Diagnostics Based on Interlevel Relationships

The dynamic properties as identified in the above section describe the process at different levels of aggregation. The global properties describe the highest aggregation level: of the process as a whole. The local properties presented earlier describe the process at the lowest level of aggregation: the specific basic mechanisms. These properties are

logically related in the sense that if a trace satisfies all local properties, then it also satisfies the global properties. To analyze these logical relationships between properties at different aggregation levels more systematically, properties at an intermediate aggregation level have been defined: the intermediate properties. Thus, a set of properties at different aggregation levels was obtained that forms a connected set of properties with the following interlevel relationships:

EP1(t1, t2, E1, E2) & GP2(W, m) ⇒ GP1(W, m)
GP3(d, e) & LP6 ⇒ GP2(W, m)
IP1(d, e) & IP2 & IP3 ⇒ GP3(d, e)
LP7 ⇒ IP1(d)
LP1 & LP2 ⇒ IP2
LP3 & LP4 & LP5 ⇒ IP3

The interlevel relationships are depicted by an AND-tree in Figure 7. Here, a property at a parent node is implied by the conjunction of the properties at its children nodes.

The interlevel relations as depicted in Figure 7 provide a formalization of a basis for a form of diagnostic reasoning that is sometimes applied in therapy practice. This reasoning runs as follows. Suppose the top-level property GP1 fails (e.g., *nonstable weight*). Then, due to the logical interlevel relations, one level lower in the tree either EP1 fails (e.g., strongly fluctuating metabolism) or GP2 fails. Suppose GP2 fails. Then, one level lower, either LP6 fails (e.g., insufficient food uptake by digestion) or GP3 fails. Suppose GP3 fails. Then, IP2 fails (e.g., no effect of eat norm on eating), IP3 fails (e.g., eating no adequate food in the sense of energy content), or IP1 fails. Suppose IP1 fails. Then, LP7 fails (e.g., no adequate adaptation mechanism of eat norm to energy use). Subsequently, the type of failure of LP7 can be identified, depending on whether weight is systematically too low or decreasing (first-phase anorexia), too high or increasing (first-phase obesitas), or fluctuating (first-phase bulimia). This can be found by checking property GP1a, GP1o, or GP1b, respectively (see section 6.2).

The above example shows the benefits of establishing interlevel relationships between properties at different aggregation levels of an adaptive dynamic process: they contribute to a formal theory that describes which local mechanisms of the process under analysis yield which global behavior. The idea is that, if the local properties of a certain process have been formalized in enough detail, then for any global property, interlevel relationships can be found that relate it to the local properties. However, finding such interlevel relationships may be a difficult task due to high complexity of the process. Therefore, this process is currently performed by hand, in a way that is similar to proof methods in mathematics. Nevertheless, work is in progress to provide automated support for the identification of interlevel relationships. Moreover, for part of this process (the verification of a property against a given trace), software is already available. This software is described in more detail in the next section.

8. Verification

Two software environments have been developed to support the research reported here. First, a simulation environment has been used to generate simulation traces, as shown in section 5. In addition, a software environment has been developed that enables us to check dynamic properties specified in TTL against simulation traces [15]. This software environment takes a dynamic property and one or more (empirical or simulated) traces as input and checks whether the dynamic property holds for the traces. Traces are represented by sets of Prolog facts of the form

```
holds(state(m1, t(2)), a, true)
```

where m1 is the trace name, t(2) time point 2, and a is a state formula in the ontology of the component's input. It is indicated that state formula a is true in the component's input state at time point t2. The program for temporal formula checking basically uses Prolog rules for the predicate set that reduces the satisfaction of the temporal formula to the satisfaction of atomic state formulas at certain time points, which can be read from the trace representation. Examples of such reduction rules are as follows:

```
sat(and(F,G)) :- sat(F), sat(G).
sat(not(and(F,G))) :- sat(or(not(F), not(G))).
sat(or(F,G)) :- sat(F).
sat(or(F,G)) :- sat(G).
sat(not(or(F,G))) :- sat(and(not(F), not(G))).
```

Using automatic checks of this kind, many of the properties presented in this article have been checked against traces such as shown in section 5. The results of these checks are as depicted in Table 1.

For the properties mentioned in Table 1, the parameters used were as follows: W = 60, E = 8, m = 0.02, d = 0.1, and e = 24. Here the first three traces are those depicted in Figures 2, 4, and 6, respectively (normal, anorexia, and bulimia). In traces 2 and 3, the adaptation mechanism is

Table 1. Results of checking properties against traces

	Trace 1	Trace 2	Trace 3	Trace 4	Trace 5
EP1	+	+	+	+	+
EP2	+	+	+	+	+
GP1	+	−	−	−	−
GP2	+	−	−	−	−
GP3	+	−	−	+	−
IP1	+	−	−	+	+
IP2	+	+	+	+	+
IP3	+	+	+	+	−
LP1	+	+	+	+	+
LP2	+	+	+	+	+
LP3	+	+	+	+	−
LP4	+	+	+	+	+
LP5	+	+	+	+	+
LP6	+	+	+	−	+
LP7	+	−	−	+	+

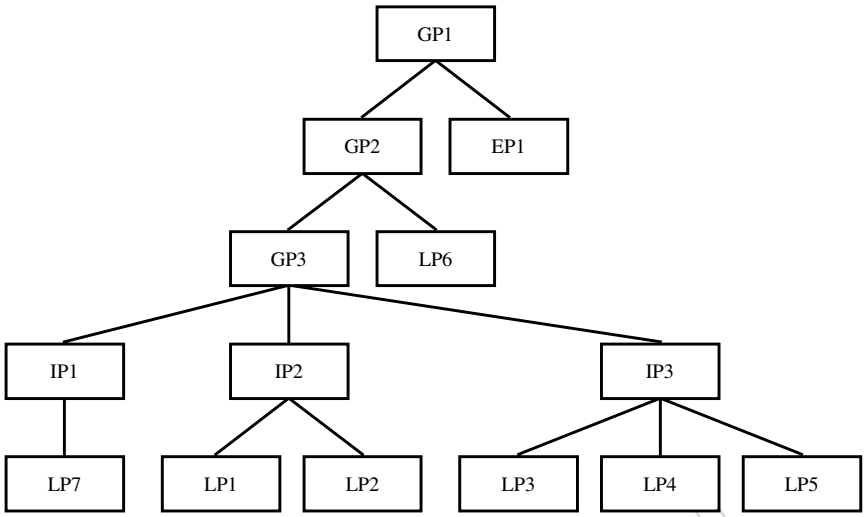

Figure 7. Interlevel relations between the dynamic properties

malfunctioning (LP7 is the cause of the problems). Trace 4 shows a pattern in which the eating regulation in principle functions well, but there is insufficient food uptake by digestion (LP6 is the cause of the problems), whereas trace 5 shows a pattern in which the response on the eat stimulus is eating food without energetic value (LP3 is the cause of the problems). Notice that indeed, for all these traces, the interlevel relations of Figure 7 hold.

9. Relation with Dynamical Systems Theory

As mentioned earlier, traditionally, analysis of dynamical systems is often performed using mathematical techniques such as the DST, put forward, for example, in Port and van Gelder [1]. The question may arise whether such modeling techniques can be expressed in TTL. In this section, it is shown how modeling techniques used in the dynamical systems approach, such as difference and differential equations, can be represented in TTL. First, the discrete case is considered. An example of an application is the study of the use of logistic and other difference equations to model growth (and, in particular, growth spurts) of various cognitive phenomena (e.g., the growth of a child's lexicon between 10 and 17 months; cf. [16, 17]). The logistic difference equation used is the following:

$$L(n + 1) = L(n)\ (1 + r - r\ L(n)/K).$$

Here, r is the growth rate and K the carrying capacity. This equation can be expressed in our temporal trace language on the basis of a discrete time frame (e.g., the natural numbers) in a straightforward manner:

$$\forall\ t$$
$$\text{state}(\gamma\ , t) \models \text{has\_value}(L, v) \Rightarrow$$
$$\text{state}(\gamma\ , t + 1) \models \text{has\_value}(L, v\ (1 + r - rv/K))$$

The traces γ satisfying the above dynamic property are the solutions of the difference equation. Another illustration is the dynamical model for decision making presented in Busemeyer and Townsend [18] and Townsend and Busemeyer [19]. The core of their decision model for the dynamics of the preference P for an action is based on the differential equation

$$dP(t)/dt = -s\ P(t) + c\ V(t),$$

where s and c are constants, and V is a given evaluation function. One straightforward option is to use a discrete time frame and model a discretized version of this differential equation along the lines discussed above. However, it is also possible to use the dense time frame of the real numbers and to express the differential equation directly. To this end, the following relation is introduced, expressing that x = dy/dt:

$$\text{is\_diff\_of}(\gamma, x, y) :$$
$$\forall t,w\ \forall \varepsilon > 0\ \exists \delta > 0\ \forall t',v,v'$$
$$0 < \text{dist}(t',t) < \delta\ \&\ \text{state}(\gamma, t) \models \text{has\_value}(x, w)$$
$$\&\ \text{state}(\gamma, t) \models \text{has\_value}(y, v)$$
$$\&\ \text{state}(\gamma, t') \models \text{has\_value}(y, v')$$
$$\Rightarrow \text{dist}((v' - v)/(t' - t),w) < \varepsilon$$

where dist(u,v) is defined as the absolute value of the difference (i.e., u – v if this is ≥ 0 and v – u otherwise). Using this, the differential equation can be expressed by

$$\text{is\_diff\_of}(\gamma, -\ s\ P + c\ V, P)$$

The traces γ for which this statement is true are (or include) solutions for the differential equation. Models consisting of combinations of difference or differential equations can be expressed in a similar manner. This shows how modeling constructs often used in DST can be expressed in TTL. Thus, TTL subsumes modeling languages based on

differential equations but enables the modeler to express more qualitative, logical concepts as well.

10. Discussion

To analyze the disorders of their patients, psychotherapists often have to get insight in adaptive dynamical systems. Analysis of dynamical systems usually is performed using mathematical techniques such as DST [1]. Many convincing examples have illustrated the usefulness of DST; however, they often only address lower-level cognitive processes such as sensory or motor processing. Areas for which a quantitative approach based on DST offers less are the dynamics of higher-level processes with mainly a qualitative character, such as reasoning, complex task performance, and certain capabilities of language processing. The type of reasoning performed in psychotherapy practice often combines such qualitative aspects with more quantitative aspects. To support this type of reasoning, in this article, a novel approach was presented to analyze adaptive dynamical systems within psychotherapy. The approach is based on the specification of (local and global) dynamic properties in a high-level (logical) language that combines qualitative and quantitative concepts. Using this language, an executable model has been developed of the dynamics of eating regulation disorders.

The model was inspired by the theory of Delfos [9], where it is assumed that the cause of the eating disorder is primarily in the biological mechanism (the adipostat). Following this theory, our model gives a good basis for therapeutical reasoning. The biological problem is that the adipostat does not function properly. According to our model, this function comprises the pattern that generates the eat stimuli based on an eat norm (LP1 and LP2 in the simulation model) and the adaptive pattern that adapts the eat norm to the circumstances (LP7 in the simulation model). When the adipostat malfunctions, the improper functioning of the adaptation process can be corrected by training. In terms of the simulation model, the problem is that in property LP7, if $\beta < 1$, the eat norm does not become high enough (as with anorexia), and if $\beta > 1$, the eat norm becomes too high (as with obesitas). This parameter is to be accommodated, which can be done by training (of the client) to learn to pay more attention to the balance between food and activity (per day), thus developing a more accurate monitoring of what the body takes in and what it needs. By checking weight every day, feedback can be obtained. Thus, the adipostat is accommodated to a better functioning adaptation process.

To analyze the model, a number of simulation traces have been generated, both for well-functioning situations and for different types of malfunctioning situations that correspond to the first phase of well-known disorders such as anorexia (nervosa), obesitas, and bulimia. Moreover, it was shown how such traces can be automatically analyzed against global dynamic properties and how the establishment of interlevel relations between dynamic properties can be useful for diagnostic reasoning.

The high-level model has proven its value by predicting and explaining many of the patterns observed in psychotherapy practice. As one example, the development of obesitas after age 35 can be explained as a lack of adaptive properties of the system with respect to a decreased metabolism level. A more detailed model based on a set of differential equations for more detailed physiological processes is hard to obtain due to the lack of detailed knowledge (and parameter values) at the physiological level. Furthermore, even if such a model could be constructed, it probably would be so complex that it is hard to handle for simulation and analysis. Moreover, such mathematical techniques are not compatible with the type of reasoning within psychotherapy practice.

In comparison to classical temporal languages such as LTL**[*PLS. SPELL OUT*]** and CTL**[*PLS. SPELL OUT*]** (see, e.g., [20, 21] and Temporal Logic [22]), our analysis approach has possibilities to incorporate (real or integer) numbers in state properties and in the timing parameters e, f, g, h. Furthermore, TTL has more expressive power than these languages. For example, explicit reference can be made to (real) time, and variables can be used. Moreover, reference can be made to different developments of processes over time; thus, statements such as "exercise improves skill," which require comparison of different histories, can be formalized.

In comparison to rule-based (simulation) approaches such as described by Holland [23] and Rosenbloom, Laird, and Newell [24], our LEADSTO format is more declarative in a temporal sense: in a built-in manner, the simulation processes are explicitly related to (and have their semantics in) the (real) time dimension, and that relationship to time does not depend on the computational processes in an implicit manner, as is usual in rule processing. Furthermore, in our approach, a format is available to express more complex, nonexecutable dynamic properties in our language TTL, and analysis methods for these dynamic properties at different aggregation levels are available as described above.

Further work is under way to show in more detail how, for cases of a malfunctioning system, the types of therapy described in Delfos [9] can lead to a modified dynamical system in which eating regulation is functioning well.

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