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Towards a second cybernetics model for cognitive systems

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Abstract

We introduce an adaptive system for dynamics recognition. Thereby, an externally presented dynamics (stimulus) is mapped onto a mirror dynamics which is capable to simulate (simulus). A sudden change of the external dynamics leads to an surprisingly quick re-adaptation of the simulus, even if the presented dynamics is chaotic. The system consists of an internal pool of dynamical modules. The modules are forced to the latter dynamics in the sense of Pyragas' control mechanism by the stimulus. The control term, i.e. the strength of forcing, is used as a measure for which modules fit best to the external dynamics. In a sense, this defines a "dynamics-gradient" within the pool. The mirror dynamics now can be constructed by a linear combination of the best fitting modules with weights given by the control term amplitudes. If one adds the so-constructed mirror dynamics to the pool, one has a representation of the corresponding external dynamics within the pool. Later if the same external dynamics is presented again an even quicker adaptation is possible since a well-fitting module is already present. In order not to blow up the dimensionality of the pool, one can eliminate modules that have not been used for a long time. In principle, the modules can undergo an internal control. In addition, one principally can introduce evolution within the pool. Therefore, the system is able to show what sometimes is called a "second cybernetics", i.e. a hyper-dynamics of the dynamics modules.

1. Introduction

Assume a car coming along a street which you want to cross. The brain is able to give extremely good estimations whether you can safely cross the street before the car approaches or whether you better wait until it has passed. Therefore, the brain has to have a simulation capability (simulus) [1,2]. However, quite frequently you also have to react to sudden changes of the external dynamics. This in turn necessitates a quick re-adaptation of the simulus. If a gazelle wants to escape from a hunting-leopard it has to perform the dynamics changes more vehemently than the predator can adapt its simulus and react accordingly [3–6].

Guided by the above aspect of brain dynamics we present a system which mimics such a behavior. The scheme of our system is depicted in Fig. 1. To the left, we have an external dynamics which is "perceived" by the system (stimulus). To the right, we see the representation of the external dynamics as a "mirror". This dynamics is the simulative part of the system (simulus). However, the kernel of the system is a pool of dynamical modules each of which is controlled by the external dynamics. The strength of the control term, which is explained in detail in the following section, serves as a measure of "fitness" of the corresponding module. The modules are used in a superpositional manner to build up the simulus weighted by their fitness. In the scheme depicted in Fig. 1 the modules D_3 and D_4, for example, fit best to the stimulus and, therefore, contribute with a larger weight (bold arrows) to the construction of the simulus. D_1 and D_6, for example, fit worse and contribute less (dashed arrows) to build up the simulus.

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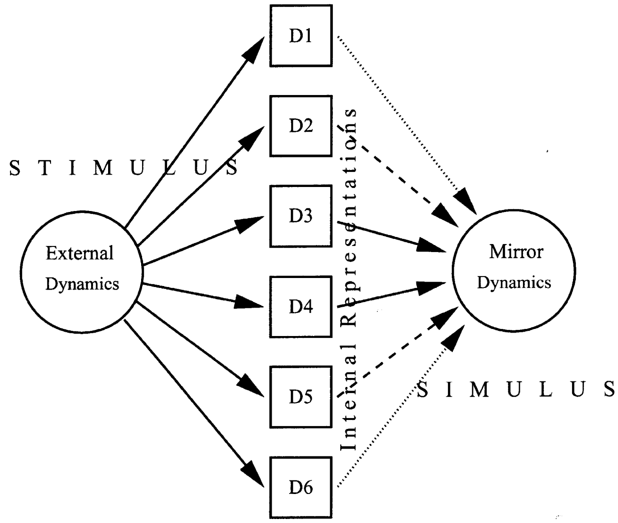

Fig. 1. Scheme of the adaptive system.

We emphasize that the adaptation is done "on the fly". We do not have to record a long time series of the external dynamics and analyze it by means of established time series analysis which is far too slow for the purpose of an instantaneous response. In addition, common methods rely on a stationarity of the external dynamics on a rather long run.

In Section 2 we present the mechanism for the "perception" which is performed on the basis of the so-called Pyragas external force control [7]. In Section 3 we present an example of how the system works by using an external time series computed from the Rössler system. In this first illustrative example we assume that the dynamics is known except one parameter that has to be estimated. In the subsequent Section 4 two possible mechanisms for the construction of a mirror system (simulus) are presented. The first one has already been published [8,9] and is briefly recapitulated here. It uses information from the recent history to construct the mirror system. The second mechanism which we here propose for the first time works without any information from the past. This method is a "real-time" method in a narrow sense.

However, as we show in Section 5, the method can be applied also to time series analysis in a more traditional sense where a record is available. The result is extremely convincing since we are able to "fit" models to chaotic time series which is almost impossible by means of established regression procedures such as least squares or other maximum likelihood approaches using simplex methods for the optimization, for example. For the introduction to such an application we mimic a sparse time series by an artificial dilution of the external Rössler signal. In Section 6, an application to a real measured time series, namely a human pulse signal, is discussed. Once adapted to a time series the model can again be used for a real-time application. That is, for example, if the person whose pulse is measured performs some gymnastic activity during the measurement, the according parameter's time course of the model can be visualized on a screen without a storage of the signal. That is, the cognitive system is able to react instantaneously in case that the external dynamics changes. Finally, in Section 7 we give a hint for a possible mechanism how to introduce dynamics within the pool of internal dynamics, i.e. a second cybernetics application. We suggest possible mechanisms to adapt not only within a given family of dynamics but rather between different types of dynamics.

2. Brief recapitulation of Pyragas' control method

The external force control method introduced by Pyragas [7] in its original form deals with the stabilization of unstable periodic orbits in nonlinear dynamic systems in the chaotic regime. Control is achieved by adding a "control term" (which is proportional to the difference between a variable of the system and the corresponding projection of the unstable periodic orbit to be stabilized) to the corresponding differential equation of the system. This method is able to stabilize unstable periodic orbits of the system with an – on the long run – vanishing control term.

In the following we deviate slightly from this original application by using Pyragas' control method for synchronization of two dynamical systems and refraining from being able to stabilize with an almost vanishing control term.

Assume $\mathbf{x}$ and $\mathbf{x}'$ to be the states of two dynamical systems of the same dimension n and the same dynamics $\mathbf{f}$ which are given by the differential equations:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x};\beta), \quad \beta = (\beta_1, \beta_2, \ldots, \beta_m), \\ \dot{\mathbf{x}}' &= \mathbf{f}(\mathbf{x}';\beta'), \quad \beta' = (\beta'_1, \beta'_2, \ldots, \beta'_m), \end{aligned} \tag{1}$$

where β and β' are sets of fixed parameters. If now the difference of at least one pair of corresponding variables (say the first) multiplied by a suitable chosen factor K is added to the unprimed system

$$\begin{aligned} \dot{x}_1 &= f_1(x_1, x_2, \ldots, x_n; \beta) + K(x'_1 - x_1), \\ \dot{x}_2 &= f_2(x_1, x_2, \ldots, x_n; \beta), \\ &\vdots \\ \dot{x}_n &= f_n(x_1, x_2, \ldots, x_n; \beta), \end{aligned} \tag{2}$$

this unprimed system will be forced to the dynamics of the primed controlling system, at least if the difference of the dynamics is not too extreme [10]. The value of the control term $K(x'_1 - x_1)$ may be used as a measure for the quality of the control. As in the original application of Pyragas' method, this control term will be negligible in a long term if the difference of the system parameters is relatively small.

3. The internal modules of the adaptive system

In a first approach we use a time series computed from the x-variable of Rössler's system [11]

$$\begin{aligned} \dot{x}_E &= -y_E - z_E, \\ \dot{y}_E &= x_E + 0.2 y_E, \\ \dot{z}_E &= 0.2 + x_E z_E - \alpha_E z_E \end{aligned} \tag{3}$$

as a given external signal. The subscript E refers to "external". The parameter α_E is fixed at 5.9 in a first step which leads to a chaotic attractor. The time series produced by the x-variable is shown in Fig. 2. One sees a transient phase of about 20 time units in the beginning which roughly corresponds to four cycles of the oscillator.

Now we choose $n = 6$ further Rössler systems with parameters

$$\begin{aligned} &\alpha_1 = 5.75, \quad \alpha_2 = 5.81, \quad \alpha_3 = 5.86, \\ &\alpha_4 = 5.91, \quad \alpha_5 = 5.94, \quad \alpha_6 = 5.99 \end{aligned} \tag{4}$$

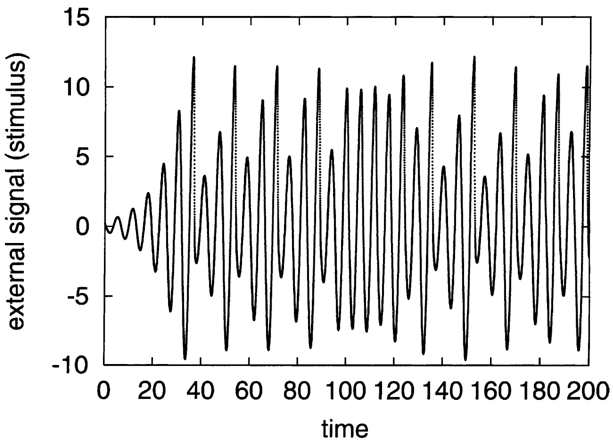

Fig. 2. External time series (stimulus) computed from the x-variable of Rössler's system. After a transient time of about 20 time units the system approaches its chaotic attractor.

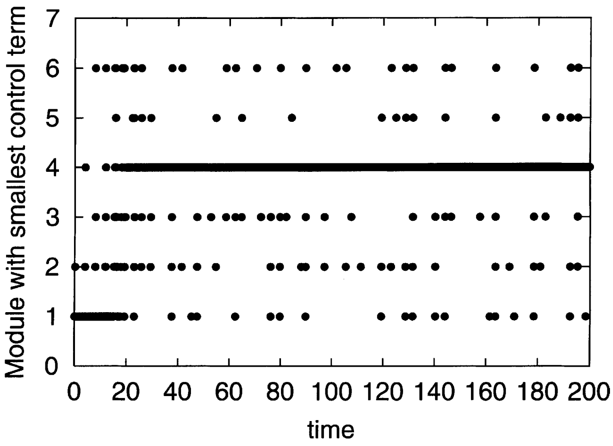

Fig. 3. Index of the module out of the internal pool which has the smallest control term versus time. After the transiency in the beginning the module switched on most frequently is system 4 which has the parameter closest to that one of the external (stimulus) system. The other events occur rarely.

to constitute a pool of internally given dynamics modules. Each of these internal dynamics is forced to the external time series by means of

$$\begin{aligned} \dot{x}_i &= -y_i - z_i + K(x_E - x_i), \\ \dot{y}_i &= x_i + 0.2y_i, \\ \dot{z}_i &= 0.2 + x_i z_i - \alpha_i z_i, \quad i = 1, \ldots, n, \end{aligned} \tag{5}$$

where K is a coupling constant which is chosen to be 1 in the following and n is the number of modules within the internal pool ($n = 6$ in this example).

At each time-step ($\Delta t = 0.01$ throughout the paper) of the numerical integration of the differential equation, we compute the absolute values of the six control terms, i.e. $|x_E - x_i|$. Fig. 3 shows the index (corresponding to the subscripts used in Eq. (4)) of the dynamics that has the smallest control term versus time. One clearly sees that after the transient time, the most frequently chosen module is system 4, i.e. the system with the parameter value closest to that one of the external signal. This indicates that the control term is a measure for the "distance" of the internal module to the external dynamics.

The initial conditions of system 1 have been chosen equal to that one of the external system which explains that system 1 has the smallest control term in the beginning. Fluctuations cause a negligible amount of events where the minima are found in the other systems. These rare events can easily be suppressed by using a moving average of the absolute value of the forcing term over, say, three time-steps. Since we focus here on the basic properties of the adaptive system, we skip this fine tuning.

One can use the "switched-on" dynamics, i.e. that one with the temporarily smallest control term, to reconstruct the attractor of the external Rössler system by using the temporarily produced trajectory pieces, for example. However, since our goal is to construct an adaptive system with simulation capability, we instead create a new element within the internal pool of dynamics that mimics as precisely as possible the external dynamics.

4. Creation of a mirror dynamics

Recently, we proposed a creation mechanism for a simulating module which uses the recent history of the control process [8,9]. We briefly recapitulate this mechanism before we introduce an alternative approach which works without any information from the past in fulfillment of a recently published suggestion [12].

To create a new element within the pool of internal dynamics as a mirror of the external dynamics, we use the relative frequency p_i of the switched-on dynamics to compute a continuous update of the parameter value of the new system through a linear combination given by

$$\alpha_M(t + \Delta t) = p_M(t)\alpha_M(t) + \sum_{i=1}^{n} p_i(t)\alpha_i(t) \quad \text{with } p_M(t) + \sum_{i=1}^{n} p_i(t) = 1. \tag{6}$$

Thereby, the subscript M refers to the mirror system with parameter α_M. The mirror system itself participates at the "competition" and is thus able to confirm its own parameter value α_M if it has a high switch-on probability p_M.

Since it is neither practicable nor plausible in the sense of a "natural" application to use the whole history, we estimate p_i and p_M, respectively, by means of a moving average over the recent past, say 10 time-steps, which corresponds to a time interval of length 0.1. As we have shown in [8,9], a large change in the value of α_M desynchronizes the mirror system and the external one for a while so that the neighbored systems have smaller control terms within that period which in turn deadjusts α_M. Therefore, we introduced a limitation of the parameter changes of α_M. If one truncates the absolute change of α_M as given by Eq. (6) to a maximum of 0.0002, this leads to a highly significant reduction of the otherwise caused fluctuation. Please confer [8,9] for details.

Fig. 4 shows the temporal behavior of the newly created parameter α_M compared to the constant parameter α_E of the external system. We observe an extremely quick adaptation, however with a slight over-estimation of the parameter value. In the aforementioned papers [8,9] we have shown that the adaptation works in a highly satisfactory manner even if the external Rössler system undergoes sudden changes. Please confer our previous work for a discussion of the over-estimation which is due to the nonlinearity of the system. Remarkably, the adaptation is performed within roughly one cycle of the oscillator and, in addition, it also works when two parameter values are unknown.

Now we introduce an alternative mechanism which works without any information from the past. The idea is to use the reciprocal absolute values of the control terms as measures of "correctness" of the corresponding modules. That is, an update of $\alpha_M(t)$, namely $\alpha_M(t+\Delta t)$, is expected to be a linear combination of the form

$$\alpha_M(t+\Delta t) \propto \frac{s}{C_M(t)}\alpha_M(t) + \sum_{i=1}^{n} \frac{1}{C_i(t)}\alpha_i(t) \tag{7}$$

together with a proper normalization. Hereby, the $C_i(t)$ (with $i \in \{1, 2, \ldots, n, M\}$) are the absolute values of the control terms, i.e. $|x_E - x_i|$, and n is the number of modules within the internal pool. The first term on the right-hand side of Eq. (7) is a "self-affirmation" term. If the constant s is greater than 1, it has a similar impact as the limitation of changes in the values of α_M as discussed above namely to avoid the onset of a large fluctuation of the value of α_M.

The translation into a differential equation leads to the following time behavior of α_M:

$$\dot{\alpha}_M = \frac{\sum_{i=1}^{n}(1/C_i(t))(\alpha_i(t) - \alpha_M(t))}{(s/C_M(t)) + \sum_{i=1}^{n}(1/C_i(t))}. \tag{8}$$

Of course, one has to take care that each C_i has a finite value by using $C_i(t) = \max\{\varepsilon, |x_E - x_i|\}$, for example, with a small ε chosen to be 10^{-30} in the following. As already mentioned, the constant s in Eq. (8) is a self-affirmation parameter which gives the parameter of the mirror system a certain weight to sustain.

In the subsequently presented simulation we use a pool which consists of $n = 10$ modules. The parameters of these modules have been chosen to be (from α_1–α_{10}): 5.71; 5.76; 5.81; 5.86; 5.92; 5.96; 6.01; 6.06; 6.11; 6.16. The external parameter has been chosen to be $\alpha_E = 5.9$, as before.

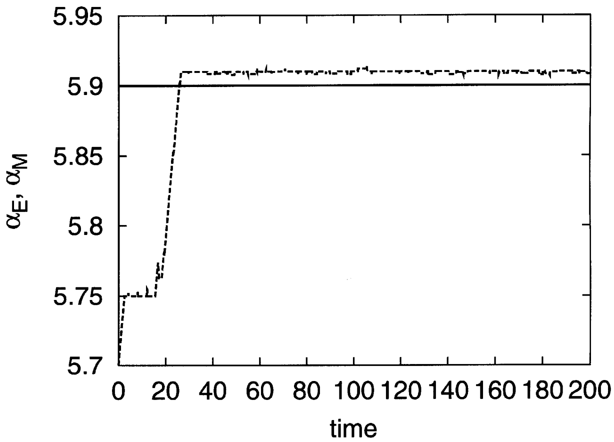

Fig. 4. Parameter adaptation in the mirror system using information from the recent history (cf. text). The mirror parameter has an initial value of $\alpha_M = 5.7$. The external parameter is fixed to $\alpha_E = 5.9$. We observe a slight over-estimation.

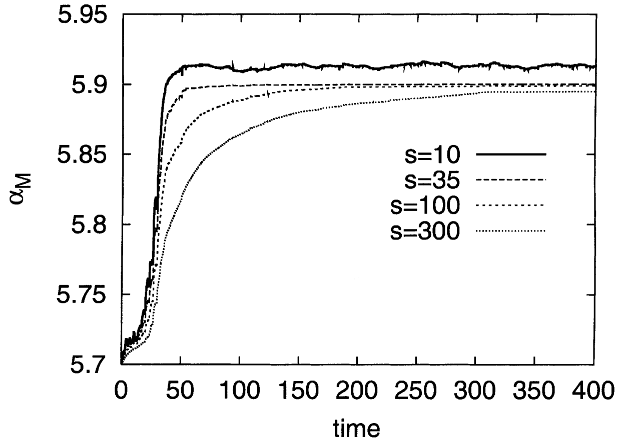

Fig. 5. Parameter adaptation using the differential equation (8) without information from the past. The values of the self-affirmation parameter have been chosen to be $s = 10$, 35, 100 and 300, respectively, which are marked correspondingly in the graph. An increasing value for s leads to a smoother curve on the cost of adaptation velocity.

As can be seen in Fig. 5, the mechanism works even better than the above-described "history method". To demonstrate the impact of the self-affirmation parameter s we present the results of four adaptation runs with $s = 10, 35, 100$ and 300, respectively. A value of $s = 10$ leads to a sustaining oscillatory behavior of α_M as well as to an over-estimation. A value for s greater than 35 leads to an accurate adaptation. The velocity of convergence decreases if s increases further.

5. Application to the analysis of sparse data

The main goal of our system is the instantaneous adaptation to a presented external dynamics in order to respond to it. However, it is also suitable for time series analysis where a record of data is available.

Usually, in measured time series one is faced with the problem of having either a large temporal spacing of data points or a too short time series or even both. To investigate a possible application within the fields of time series analysis, we stick with the Rössler model as a (simulated) source of measurement. In contrast to the above adaptation procedure we now mimic a sparse sampling rate by using only every 20th data point which corresponds to a temporal spacing of $\Delta t = 0.2$ time units or roughly 20 data points per cycle of the oscillator. In other words, the control term in Eq. (5) is active only if a data point is available. In such a case a tendency to a fluctuating time behavior of α_M can be observed which is reducible with a larger self affirmation, say $s = 5000$. However, this in turn reduces the velocity of convergence, so that a relatively short time series may not be adapted at least if the possible range of the parameter to which we want to adapt is wide. We can tackle this problem by a repeated adaptation procedure which is possible in this case since we have a record available.

The result can be seen in Fig. 6, where we repeated the adaptation 10 times. The first adaptation run leads to the lower curve of Fig. 6 for $\alpha_M(t)$. The second curve from the bottom corresponds to the second run and so on. We see a quite accurate convergence to the correct parameter value $\alpha_E = 5.9$ with a negligible remaining fluctuation. This remaining fluctuation can be reduced even more by a new adjustment of the parameter spacing within the pool, which will be discussed in the following section where we deal with an application to a real measured time series.

6. Application to a measured time series

Fig. 7 shows a short window of a measured human pulse signal to which we apply the adaptive system in the following. The temporal resolution of the measurement is $\Delta t = 10$ ms. That is, we directly identify the time-step ($\Delta t = 0.01$) of the numerical integration of the differential equations with the time-step of the measurement. Therefore, the time scale in this section is given in seconds. We use a time series with total length of $t_{end} = 90$ s. The signal is measured in mV which, however, is unimportant here.

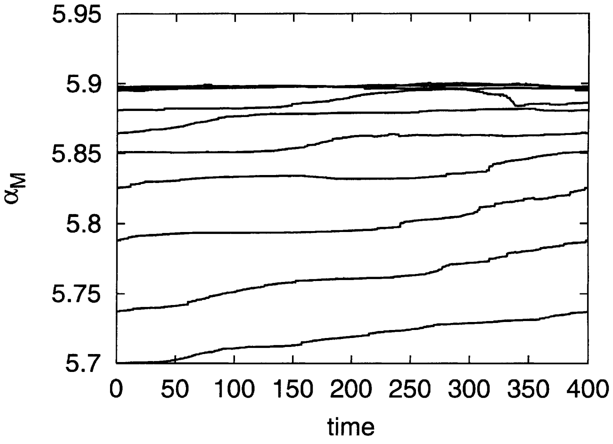

Fig. 6. Repeated parameter adaptation in the case of a sparse time series. The initial parameter value of the mirror system has been chosen to be 5.7. Ten repeated adaptation runs lead to a convincing adaptation to the correct value of 5.9.

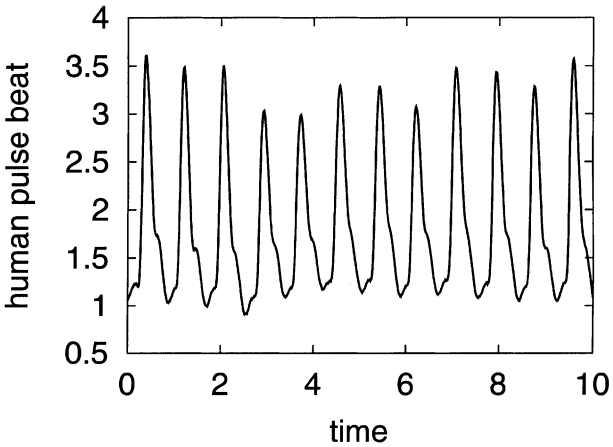

Fig. 7. A measured human pulse signal in arbitrary units (representing the blood density measured by an infrared sensor). Time is given in seconds.

As a model dynamics we use the "van der Pol oscillator" given by

$$\begin{aligned} \dot{x} &= y, \\ \dot{y} &= -\beta_0 x + \left(\beta_1 - x^2\right) y. \end{aligned} \tag{9}$$

From a physiological point of view this model may not be the best choice. However, we here focus on the substantial steps for the application of the adaptive system and it may suffice to have two meaningful parameters that allow for a detection of the corresponding physiological entities. The first parameter, β_0, is mainly related to the frequency and the second one, β_1, reciprocally to the amplitude, although both parameters are not fully independent of each other.

The explicit differential equations that are to be solved read

$$\begin{aligned} \dot{x}_i &= y_i + K(x_E - x_i), \\ \dot{y}_i &= -\beta_{0,i} x_i + \left(\beta_{1,i} - x_i^2\right) y_i, \quad \text{where} \quad i = 1, \ldots, n, M, \end{aligned} \tag{10}$$

$$\dot{\beta}_{j,M} = \frac{\sum_{i=1}^{n} (1/C_i(t)) \operatorname{sign}\left(\beta_{j,i} - \beta_{j,M}\right)}{(s/C_M(t)) + \sum_{i=1}^{n} (1/C_i(t))}, \qquad j = 0, 1 \tag{11}$$

with

$$C_i(t) = \sum_{k=0}^{p(t)} K|x_{\rm E}(t-k\Delta t) - x_i(t-k\Delta t)|, \text{ where } \quad i = 1,\ldots,n,M; \quad p(t) = \min\left\{p_0, \frac{t}{\Delta t}\right\}. \tag{12}$$

The differential equations (10) are the n (chosen to be 40) internal systems and the mirror system that are controlled by the external time series using a coupling constant of $K = 1$. The differential equations (11) that describe the parameter adaptations of the mirror system slightly deviate from the form chosen above in Eq. (8), namely we here use the sign of the parameter difference which has proven to be more stable. The self-affirmation s is chosen to be 1000 in the sequel. The control terms C_i in Eq. (11) are computed as cumulative entities from the control terms of the recent past, where p_0 is a history parameter chosen to be 10 (time-steps).

In order to adapt the parameters $\beta_{j,i}$ of the internal pool to the given time series we use the following iterative approach:

$$\begin{aligned}
&\beta_{1-(q \bmod 2),i}(t,q) = \beta_{1-(q \bmod 2),M}(t_{\rm end}, q-1) \quad \text{ for all } t \in [0, t_{\rm end}], \;\; i = 1,\ldots,n,\\
&\beta_{q \bmod 2,i}(t+\Delta t, q) = \beta_{q \bmod 2,M}(t,q) + 0.05\Big(i - \frac{n}{2} - 1\Big)\beta_{q \bmod 2,M}(t,q) \quad \text{for all } t \in [\Delta t, t_{\rm end}], \quad i = 1,\ldots,n,\\
&\beta_{j,M}(t=0, q+1) = \beta_{j,M}(t_{\rm end}, q) \quad j \in \{0,1\}, \;\; q \geqslant 0,\\
&\beta_{j,M}(t_{\rm end}, -1) = \beta_{j,M}(0,0) \quad j \in \{0,1\} \quad \text{for convenience,}
\end{aligned} \tag{13}$$

where $\beta_{j,i}(t,q)$ means the value of parameter β_j of the ith system of the internal pool at time t in the qth iteration ($q = 0,\ldots$). The definition of the initial values $\beta_{q \bmod 2,i}(0,q)$ is described in the text below.

To fully understand Eq. (13) we have to describe the adaptation procedure in detail that we used for the two-parameter case on hand. We guess initial values for the parameters β_0 and β_1, respectively, such that the model oscillator is in an oscillatory state. This means that the mirror system starts with these parameter values, namely $\beta_{0,M}(t=0, q=0)$ and $\beta_{1,M}(t=0, q=0)$, respectively. Then we construct a pool of $n = 40$ internal modules defined by a set of parameter values for $\beta_{0,i}(t=0, q=0)$. These parameter values are distributed symmetrically around the momentary value of the mirror parameter with a spacing being 5% of the latter value. In a first run (iteration parameter $q = 0$) over the $t_{\rm end} = 90$ s long time series the second parameter of each module is set equal to the initial guess of the corresponding mirror system's parameter, whereas the first parameter undergoes a dynamical redistribution around the temporarily estimated value of the mirror system's parameter $\beta_{0,M}(t)$.

In a second run over the whole time series the internal pool is redefined by a symmetrical parameter spacing of the second parameter $\beta_{1,i}(t=0, q=1)$ around the temporarily given corresponding mirror system's parameter $\beta_{1,M}(t=0, q=1)$. During this second run the values of the parameters $\beta_{0,i}(t, q=1)$ are fixed to the final value $\beta_{0,M}(t=t_{\rm end}, q=0)$ of the first run.

The whole procedure is repeated several hundred times until the parameters converge to a stationary value. This results in the following final parameter values:

$$\begin{aligned}
\beta_{0,M} &= 67.3326139550,\\
\beta_{1,M} &= 0.1049170026.
\end{aligned} \tag{14}$$

Obviously, the measured pulse signal includes a baseline shift that cannot be resembled by the van der Pol model oscillator in the given form of Eq. (9). Therefore, we shifted the measured values of the time series by its negative average towards the zero baseline.

The result is depicted in Fig. 8. The upper part shows the first 20 s of the time series together with the model output that has been computed using the adapted parameter values of Eq. (14). The lower part shows the final 20 s. The model dynamics starts in an initial state that does not lie on the limit cycle which is why the dynamics shows a transient phase of roughly 10 s. The frequency of the model dynamics obviously resembles the pulse frequency. With respect to the primary part of the time series (upper part of Fig. 8), the model shows a too large amplitude whereas in the final part it fits perfectly (lower part of Fig. 8). The explanation is that the final part of the time series which actually has a larger amplitude leaves the final mark with respect to the adaptation of the parameters. To counteract this behavior, one can increase the self-affirmation of the cognitive system. The more the self-affirmation s is increased, the more the model amplitude tends towards the mean amplitude of the time series.

To understand the remaining differences (e.g. the phase shift) between time series and model dynamics in Fig. 8 one should keep in mind that the purpose of the adaptation process of Eqs. (10)–(13) was merely to achieve an optimal fit of the model parameters to the global properties of the time series data. An exact modeling of the time series will in general require an additional real-time adaptation, which could be performed by the mechanism described in Eq. (8).

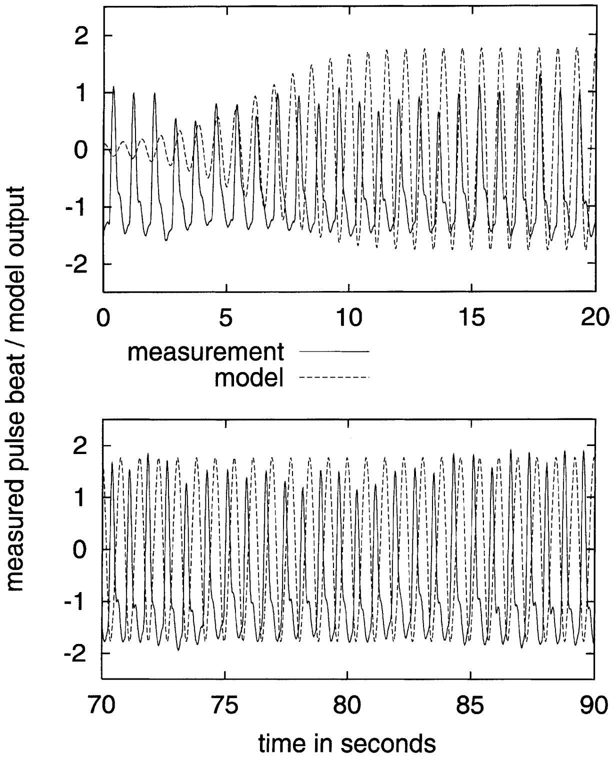

Fig. 8. Measured human pulse signal and model output compared with each other. Both the initial (upper figure) and the final part (lower figure) of 20 s length each are shown. The measured amplitude increases towards the end. Using a moderate self-affirmation parameter value for the adaptation implies that the final part determines the adapted amplitude.

It goes without saying that the number of repetitions until the parameter values converge depends on the initial guess of the parameter values. It also depends on the length of the available time series and its sampling rate as well as the choice of some system parameters such as the self-affirmation, s, or the history parameter, p_0. The concrete choice of this parameters depends on the context. We emphasize that p_0 can be chosen to be zero. However, we regard the described example as a ‘‘pre-adaptation’’ of a previously extremely vaguely defined model. In such a case an enhanced smoothness is advantageous, which can be achieved with a relatively large s and a finite p_0, respectively.

As is clear, the model dynamics never can resemble exactly the time series especially if the measured signal is chaotic. In addition, in our case we have chosen a nonoptimal model. The result can be interpreted as follows. The resulting model with the adapted parameters is one out of a family of models that has to be forced with the weakest control term towards the actual dynamics of the time series. If the family of models is the ‘‘true’’ one as in our artificial approach using the Rössler dynamics above, it is clear that the adapted mirror dynamics almost exactly resembles the correct external dynamics up to a negligible control term during the time course. In this sense the adaptation leads to the best concrete model that can be found within the given family.

In principle, we are now able to re-enter the basic idea of the adaptive system, namely to use the pre-adapted system for an instantaneous (real-time) adaptation. Our current work focuses on the implementation of an interface to read in the measured signal for such an on the fly adaptation that works without storage of the measured data. We will report the results soon.

7. Second cybernetics

Metaphorically speaking, we have a pool of simulated parallel worlds that are compared with what happens in the real world. The ‘‘fitness of matching’’ is used to create a mirror world as internal representation. The mirror itself can be fed back to the pool by removing such internal worlds that always or extremely mismatch with the real world and may, therefore, be regarded as relatively useless. Thus, the set of internal dynamics modules undergoes a continuous reconfiguration.

An interesting question is whether a cognitive system on the basis of that introduced above is capable of building any simulus. So far, the constitution of the simulus has been performed only within given families of dynamics, i.e. out of the internal pool. A first enhancement towards a generalization of the adaptive system would be to allow for combinations of modules out of different dynamics families. Recent publications on the generalization of the Rössler system [13,14] make us confident that such a generalization is possible. In this paper a modular structure of the generalized Rössler system has been proposed on the basis of linear and nonlinear modules that can be combined to build a chaotic system in arbitrarily many dimensions. It has to be checked whether this principle also works with other dynamics families and whether it is possible to fully refrain from defining a concrete family by exclusively using elementary modules. Internal control processes [15,16] and evolutionary processes then would lead to a hyper dynamics (or second cybernetics) of the pool which may eventually yield creativity at least in a technical sense. Specifically, an elementary modular adaptive cognitive system may be able to "suggest" new models that can be continuously checked by an adequate "fitness function".

The proposed adaptive system has some similarity with the Bayesian learning [17]. The Bayesian inference is used to find an aposteriori probability for the validity of a given hypothesis after a test or an experiment has been carried out. Such an update of an apriori probability, however, only yields probabilities for the predefined hypotheses. It can not create new hypotheses itself. Endowing the proposed adaptive system with the aforementioned second cybernetics via internal control and mutations very likely can overcome this restriction. It seems to be justified then to speak of an "hermeneutic engine" in accordance with Erdi [18] and Kaneko and Tsuda [19].

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